

Theoretical Vessel Valuation and Asset Play in Bulk Shipping

by

Roar Os Adland

M.S. Naval Architecture

Norwegian Institute of Technology, 1995

M.S. Business Economics

Norwegian School of Economics and Business Administration, 1998

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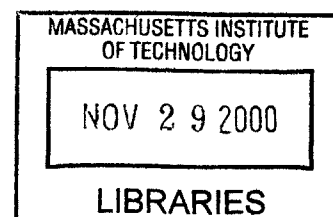
Department of Ocean Engineering
May 5, 2000

Certified by.....

Professor Henry S. Marcus
Professor of Marine Systems
Thesis Supervisor

Accepted by.....

Professor Nicholas Patrikalakis
Kawasaki Professor of Engineering
Chairman, Departmental Committee on Graduate Studies



Abstract

This thesis consists of two related parts. The first part develops non-parametric freight rate and scrap value models for the product tanker market. Monte Carlo simulations are used to calculate the value of the vessel as the present value of future cashflow and perform sensitivity analysis with respect to input parameters such as vessel age, freight rate volatility, and scrap price. The second part investigates the performance of technical trading rules for the purpose of asset play in the product tanker market. The rules are tested on monthly returns in the product tanker segment for the period 1981 to 1998. A total of 1053 different parameterizations are evaluated, comprising three of the simplest and most popular trading rules in the financial markets: filter rules, moving averages, and support and resistance levels. Overall, the results provide strong support for the technical strategies. The best-performing trading rule obtains a mean return of 35.4% p.a. above the buy-and-hold annual return of 4.0%. However, the practical implementation in an illiquid market may reduce the theoretical excess return of the best-performing trading rule to a level where it is no longer significant. Moreover, the probability that an investor could have picked, ex ante, a trading rule with statistically significant excess return is small.

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This thesis is in many ways a summary of many of my interests as a student in the Ocean Systems Management program since I started in 1998. They have been two very interesting years and I have really enjoyed the company of fellow students and my always friendly and helpful advisor Professor Henry Marcus. I am also thankful to my employer, the Norwegian School of Economics and Business Administration, and sponsor, the Norwegian Association of Shipowners, for their financial support that has given me the opportunity to study at MIT. I also have to thank the Marsoft Boston office for providing some of the data I have used in this thesis. Last but not least, I want to thank my dear wife Raina who has put up with my sometimes long working hours and having to proofread my papers.

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1 Introduction

1.1 Purpose

The purpose of this thesis is to investigate the performance of theoretical models for vessel valuation and investment decisions in bulk shipping. Furthermore, this thesis introduces non-parametric freight rate models in maritime economics, a methodology that is often used in empirical financial research but has yet to be applied to the shipping markets. By developing a theoretical vessel valuation model that is as close to reality as possible, this line of research can possibly uncover whether the second-hand market is efficient or can yield superior returns from asset play. Based on the performance of simple technical trading rules, the work attempts to answer whether simple technical trading rules can forecast future prices based on historical trends.

1.2 Overview

Chapter 2 provides a brief introduction to the dynamics of the freight and demolition markets as a background for the subsequent quantitative modeling. The chapter also provides an introduction to the sale and purchase process and the valuation of a vessel in practice. Furthermore, the empirical characteristics of the relationship between the freight rate level and vessel values are investigated.

Chapter 3 explains the background for using the present value model for vessel valuation and provides a detailed evaluation of the cost structure in bulk shipping. The embedded

real options (lay-up and scrapping) that have to be considered when valuing a vessel are also treated in detail.

Chapter 4 starts with a summary of related existing research in maritime economics and provides the theoretical background for non-parametric estimation. Subsequently, the empirical models for the timecharter rate and scrap value are developed. The additional assumptions concerning the interest rate and market price of freight rate risk are also evaluated. The last part of Chapter 4 provides an introduction to the principles of Monte Carlo simulation for asset valuation.

Chapter 5 presents the results from the theoretical valuation model, including the theoretical depreciation curve and sensitivity analysis with regards to scrap price and volatility. The results are also compared with actual market data. Alternative applications for risk management and derivatives valuation are also introduced.

Chapter 6 concerns the performance of asset play using technical analysis. The chapter first provides an introduction to technical analysis and existing financial research in this area. The problems related to data snooping and the methodology behind the evaluation of technical trading rules are treated in detail. Finally, the empirical results of the technical trading are presented.

Chapter 7 and 8 provides the conclusions of this work and suggestions for future work.

2 The shipping markets

2.1 The freight market

The freight markets in the various bulk shipping sectors are very liquid, with several fixtures of vessels taking place every day, on average. Because freight rates are the primary mechanism driving the activities of shipping investors, the mechanisms of the freight market have been the main field of interest since the beginning of maritime research. A cursory look at any long time series of freight rates suggests that they are cyclical, and the underlying economic intuition behind the mechanisms of the shipping markets supports this hypothesis. When there is too little supply, the market rewards investors with high freight rates until ships exit from lay-up and more ships are ordered. This eventually increases the supply and puts a downward pressure on the freight rates. In the case of over-supply, low freight rates result in slow-steaming ships, lay-up, or, if market prospects are very poor, owners give up and scrap the ship. This reduces the supply and contributes to market recovery. This described capacity adjustment is an important argument for mean reversion of freight rates. Since shipowners are constantly trying to second-guess the cycle, crowd psychology is believed to play an important role in this game and adds to the irregularity.

2.2 The scrap market

A ship put up for sale on the demolition market is usually bought by cash speculators who act as intermediaries, buying the ships for cash and selling them on to the demolition yards. Scrap prices are determined by negotiation and depend on the

availability for ships for scrap and the demand for scrap metal. Prices vary between geographical regions and ship types, and large tankers normally obtain a premium over bulk carriers, due to their relatively simple structure and large flat panels.

The ship-breaking industry is very mobile. In the mid-1980s, almost three quarters of the capacity was located in Taiwan, China and South Korea. Ten years later, Taiwan and South Korea had left the industry, China's market share had fallen to 9%, and India, Bangladesh and Pakistan had taken over as market leaders. The explanation is that this very basic industry gravitates towards countries with low labor costs. Currently, Vietnam and China are the emerging ship-breaking centers. The predominant method of ship demolition is still beaching, that is, the vessels are run aground and dismantled using manual labor and limited capital investments. Accordingly, the entry barriers are low and ship-breaking capacity can be easily adjusted. Also, from a purely technical point of view, productivity in terms of speed can easily be improved by introducing modern heavy machinery or increasing the workforce or worker skills. In total, the demand side of the industry possesses a large degree of elasticity. However, the growing awareness of the safety and pollution issues in the industry gradually imposes new political legislation. Requirements concerning cleaning and gas removal delay the scrapping process, and regulations on maximum number of ships per plot reduce capacity. The introduction of import duties increases the price of the ship to the ship breaker and reduces demand.

The supply of ships for scrapping depends on the freight market, as second-hand values reflect current and expected future earnings. Ships that are scrapping candidates in a depressed market may have second-hand values that far exceed the scrap value if the freight rates improve. Thus, only ships that cannot be traded, either due to regulations on age or the need for massive repairs after an accident, will usually be sold for scrapping in good markets. Accordingly, supply to the demolition market is typically very scarce when freight markets are good.

2.3 The Sale & Purchase process

A shipowner will usually put his vessel on the market using a shipbroker and indicate an asking price. Ships are usually sold by negotiation, that is to say, by offer and counter offer. These negotiations continue until the two parties reach a deal. The basics of the offer are reply time, price, delivery (time and place) and conditions of sale. It is usual to have one broker acting for the buyer and one broker acting for the seller. Except for demolition, ships are rarely purchased without being inspected by the buyer's superintendent engineer or other qualified surveyor. Prior to the survey, the ship's records are inspected at the relevant classification society. Usually dry docking is required to enable inspection below the water line. If the vessel is accepted after the inspection, the sale is finalized according to the Memorandum of Agreement drawn up by the seller's broker. Incidentally, the buyer does not have to give reasons for turning down the ship after inspection, and can simply walk away from the deal even at this stage. It happens frequently that a vessel remains for sale for a long period of time, and if the seller does not receive an offer that is high enough, he may eventually pull the

vessel from the market altogether. The characteristics of the S&P process are important to keep in mind when considering time series of vessel values.

2.4 Vessel valuation in practice

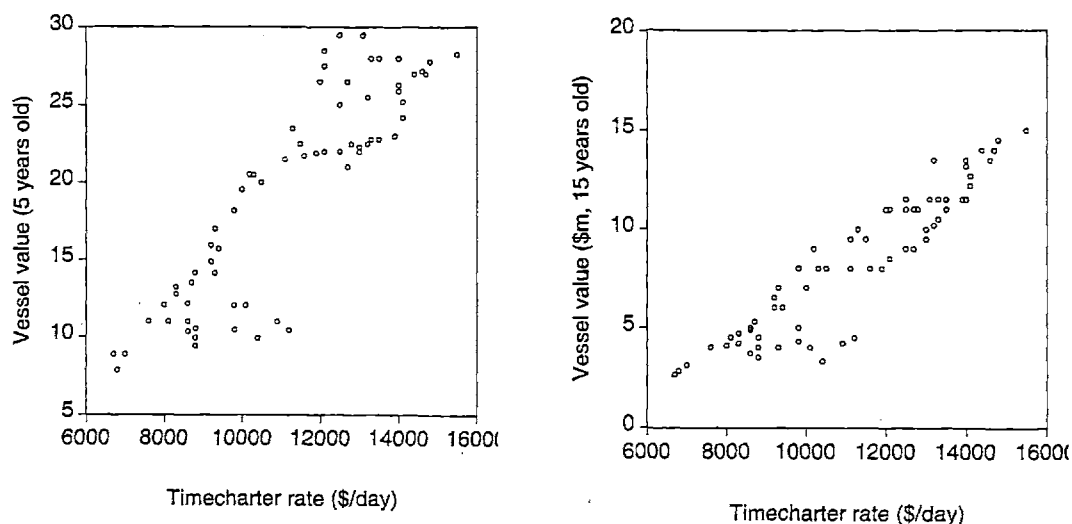
Freight rates are the primary influence on ship prices and peaks and troughs in the freight market are transmitted into the sale and purchase market. The first task of the shipbroker is to look at similar type vessels that were sold recently or are currently offered for sale. Based on this information, a suitable price per deadweight ton is established, and the appropriate value of the vessel is calculated based on its deadweight. The second influence is age. Brokers who value ships take much the same view as accountants, depreciating merchant ships down to scrap over 15-20 years, and using as a «rule of thumb» that a ship loses 5 or 6% of its value each year. The slope of the depreciation curve reflects the loss of performance due to age, higher maintenance costs, a degree of technical obsolescence and expectations about the economic life of the vessel. If the ship to be valued is two years younger than the comparable vessel, the broker adds 10%-12% for the difference in age. To this figure he would add or deduct for features such as type of gear, size of engine, place of build etc. For instance, some brokers allow a differential of 2% per knot when comparing ships. In the longer term, inflation affects ship prices. The fourth influence on second-hand values is expectation. This accelerates the speed of change at market turning points. Clearly, the valuation process is quite simplistic and subjective, and is not directly related to the expectations of future earnings.

2.5 Empirical characteristics

The second-hand markets for ships generally have a low turnover. In the large tanker category (200,000DWT+), a total of 187 vessels were reported sold in the second-hand market from January 1990 to March 1999¹, corresponding to an average annual turnover of 5% of the fleet. For smaller vessel sizes, the world fleet is larger, and, accordingly, the liquidity is better. The lack of standardization and a liquid asset market sometimes entail the use of shipbrokers' estimates for a standardized vessel in place of actual transaction data. Such historical valuation estimates are typically published on a monthly basis and consist of vessel values for, say, a five-year-old vessel. This thesis concerns the product tanker market. Product tankers are relatively small vessels (35,000 DWT - 45,000 DWT) that typically transport liquid bulk cargoes such as gasoline and fuel oil between e.g. the Caribbean and the U.S. Due to the fairly large fleet size in terms of the number of vessels, the market for second-hand vessels and timecharters is more liquid than the larger tanker sizes. The technological development has been slow and continuous, with the exception of the implementation of double-hull regulations.

Assume for a moment that the level of the one-year timecharter freight rate is the only variable that affects the value of a vessel of a certain age. Then a scatter diagram plot of the one-year timecharter rate and the second hand value should reveal a consistent functional relationship between the market value and freight rate. Quarterly quotes for a five-year-old vessel (right) and a 15-year-old vessel (left) from 1982 to 1998 are shown in the figure below.

Figure 1: Second-hand value vs. one-year timecharter rate



Data source: Marsoft

Note that these observations are not actual transactions, as the vessel characteristics and the corresponding market value vary greatly within the fleet. Instead, the estimates are based on actual transactions and re-calculated as an average for a "representative" vessel with standardized characteristics such as vessel speed, cargo capacity, fuel consumption etc. If there were few or no transactions in a given quarter, the numbers represent the shipbroker's best estimate. Of course, the methods for practical vessel valuation that were outlined above can hardly be considered "rocket science" and leave room for subjectivity. However, the data provider in this case (Marsoft Inc) is known to build their database from several other sources, reducing the potential for flaws.

¹ Source: MaritimeData.com

Even these simple diagrams lead to a number of interesting observations regarding vessel prices. Firstly, there seems to be a distinct upper limit for the price paid for a vessel at a given freight rate level. This maximum price is linear in the freight rate level. However, for a given freight rate, say \$11,000 per day, which is the average over the time period, the historical second-hand values range from \$3 million to \$9 million for a 15-year-old vessel. From what is said above, this variation can hardly be attributed to technological development or variations in the fleet. Whether this variation is consistent with an efficient second-hand market for vessels is a key question in this thesis.

Based on the results in Figure 1, the prevailing one-year timecharter freight rate is obviously not the only variable determining the vessel price. In addition, long-term expectations, as represented by the term structure of freight rates, will have an impact on valuation, and, at least for an old vessel, it is likely that changes in the scrap price will influence the vessel value. Perhaps even more important is the level of interest rates and changes in the risk premium required by investors. These variables have not been constant over the last two decades, which could explain a large part of the observed "pricing errors" in Figure 1. If there are large deviations between the fundamental value indicated by theory and the market price, it is tempting to conclude that the valuation methodology used by shipbrokers are flawed, leaving room for asset play and excess returns from investments.

3 Introduction to theoretical valuation

3.1 The present value model

Second-hand prices fluctuate in the region between newbuilding and scrap values, representing the cap and floor of the second-hand price respectively. The price of a new vessel generally represents the steel, outfitting material, and labor costs of building the vessel, along with any profit the shipbuilder may pocket. Likewise, it is easy to appreciate the scrap value of a vessel as the price the demolition yard is willing to pay for the recoverable steel and material content of the ship. Of course, in both instances one must allow room for price variation depending on the market conditions and the negotiating skills of the individual shipowner vis-à-vis the shipbuilder or scrap merchant. The only intrinsic value in the vessel, no matter what its age, is the scrap value. Any excess value represents the present value of the future cash flows the vessel is expected to earn over its remaining operating life. Consequently, the theoretical vessel value V_t can be written as a simple Present Value model:

$$V_t = \sum_{\tau=t}^T (X_{\tau} - d_{\tau}) / (1 + r_{\tau})^{\tau} + S_T / (1 + r_T)$$

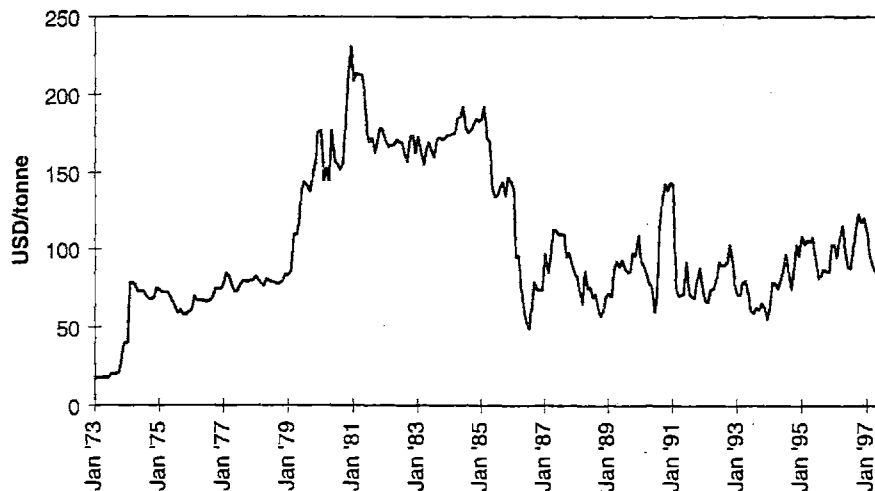
where X_{τ} is the instantaneous timecharter equivalent freight rate, d_{τ} is the operating cost, r_{τ} is the discount rate, and S_T is the scrap price at the time of demolition of the vessel. However, the simplicity stops there, as virtually all the variables are stochastic and forward looking, including the terminal date T . A major part of this thesis concerns the empirical estimation of the stochastic processes and theoretical value V_t .

3.2 The cost structure

3.2.1 Operating costs

If the freight rate process is estimated from timecharter equivalent freight rates, that is, the spot rate income on a daily basis minus voyage-related expenses (fuel costs, canal and harbor fees), the price process will include two sources of uncertainty - the spot revenue and the bunkers cost. Fuel prices are highly volatile as indicated in the figure below. The relative importance of fuel costs depends primarily on the number of days at sea vs. days in port per roundtrip, fuel efficiency, operating speed and bunkers price.

Figure 2: Bunkers price: Heavy Fuel Oil, Rotterdam (1973 - 1997)



Source: Clarkson Research

The remaining cost factors do not vary to a great extent, but nevertheless, the sum will not be constant, and is likely to increase over the lifetime of a ship. The vessel operating costs consist of:

- Crew costs (wages, social insurance, pensions, and travel expenses). The minimum number of persons onboard is given by the regulations specified by the flag of registration. A higher number of crewmembers may be a part of the shipowner's policy, e.g. in order to keep a high level of planned maintenance. The number of man-hours necessary to keep the ship in a satisfactory condition will normally increase as the ship ages due to intensified corrosion and wear and tear. The extra crew are needed to handle the repair and maintenance workload which is a continuous cycle on an old ship and which typically can be carried out more cheaply at sea. Accordingly, the crew expenses will increase, although changing the mix of high-cost and low-cost crew may compensate for this to a certain extent.
- Stores and consumable supplies (spare parts, deck and engine room equipment, cabin stores and lubricating oil). The risk of breakdown and the corresponding need for spare parts and repair is likely to increase with age. Even with extensive maintenance, the physical condition gradually deteriorates, and repair-/maintenance costs increase.
- Insurance is a cost item likely to vary much from ship to ship. A high proportion of marine insurance costs is determined by the insurance of the hull and machinery (H&M), which protects the owner of the vessel against physical loss or damage, and the Protection and Indemnity (P&I) insurance, which provides coverage against third party liabilities. The level of premium is determined by the owner's claims record, the value of the ship, intended trading area, cargo and the nationality of the crew.

- General costs. Included within the annual operating budget for the vessel is a charge to recover shore-based administrative and management charges, communications and miscellaneous costs. These depend on the type of operation.
- Periodic maintenance is a provision set aside to cover the costs of interim dry-docking and renewal surveys. In this thesis, periodic upgrading costs are included as a provision in the daily operating costs, and not accounted for as periodic lump sums.

This brief discussion indicates that a model where the operation costs (excluding voyage-related costs) increase with age is preferable. The cost structure varies between each individual ship, based on its quality, maintenance history and shipowner policy, and thus the operation costs should be modeled individually for each vessel. In this thesis it is assumed that operation costs are deterministic and time-dependent, although the repair costs due to failures and inflation clearly are stochastic variables.

3.2.2 Upgrading costs

In order for a vessel to remain in class and obtain insurance, it is surveyed periodically to make sure it complies with international safety regulations and the technical standards of its classification society. A normal survey schedule consists of a renewal survey approximately every five years and an intermediate routine survey after 2.5 years. Both surveys require dry-docking due to bottom examination. The periodical need for upgrading can have a significant impact on the supply of tonnage. Owners that are

confronted with costly rectification work may decide to lay up the vessel without a trading certificate or sell it for scrap. Even if the life of the vessel is extended, the vessel is off-hire for a longer period of time. If a shipowner decides to extend the life of a vessel beyond a renewal survey he will face the following costs:

- **Dry dock fee.** The fee for use of the dry-dock is based on the number of days for completing the survey and the corresponding upgrading, i.e. steel replacement, conversions and equipment overhaul. There is also an additional fee for the docking/undocking. Normally a part of the upgrading and survey can be done alongside a berth, in which case the fee is lower. Once a work specification from the owner is given, the yard can estimate the number of days required. However, the survey may uncover new problem areas and the need for extensive repairs, which will prolong the docking. Thus, we may consider the required time for the survey and upgrading as a stochastic variable. This is obviously a very subjective topic which will depend on the availability of dry-dock space, the condition of the vessel, and the standards imposed by owners and classification society inspectors.
- **Steel replacement costs.** This figure includes all staging and preparation work, and will vary between the different areas of steelwork and from yard to yard. The cost of steel replacement will depend on the degree of wastage, and the amount of steel that has been replaced at the previous renewal surveys. Also of vital importance is the maintenance of and the extent of corrosion protection in ballast and cargo tanks. The building yard's design specifications will also influence the extent of steel

replacement. Labor shortages could make it difficult for owners to access the most cost-effective ship repairing centers, leading to a degree of cost inflation.

- The cost of work on the main propulsion system, cargo handling equipment, auxiliaries and safety equipment, as well as upgrading to comply with maritime legislation such as Marpol 13G.
- **The alternative cost due to off-hire.** Strictly speaking, this is not only the revenue loss corresponding to the number of days in a dry-dock or alongside a berth in the repair yard, but also the «off-hire» caused by deviation from the vessel's ordinary sailing schedule. Without much loss of generality, it can be assumed that the duration of the docking is equivalent to the days off hire and that it is known a priori. When a vessel is dry-docked, the freight revenue and voyage-related expenses (bunkers, port charges etc.) are suspended, while most operational costs (crew, insurance etc.) are still running. Accordingly, the net instantaneous alternative cost is equal to the timecharter equivalent spot rate.

3.3 Embedded real options

The purchase of a vessel includes several elements of options. A shipowner has an option to lay up the ship when the freight rates are low, and put it back into operation when the market improves. The cost to take a vessel from lay-up to active trade or mothball it is in the order of \$150,000. Throughout the lifetime of the ship, the owner also has an option to scrap the vessel or sell it in the second-hand market. The options

represent flexibility of a physical asset and are therefore called “real options”. In an uncertain world they have an economic value that must be included in the asset price.

3.3.1 The lay-up option

The flexibility to lay up or «mothball» a vessel in order to limit operating losses will have a higher value for cost-inefficient operators since freight rates seldom fall below the lay-up level of the more cost-efficient operators. On an aggregate level, the ship operators influence the dynamics of the underlying stochastic freight rate by exercising the option to mothball or lay up, due to the changes in total supply. Jan Mossin (1968) discusses the optimal lay-up policy for an individual vessel, with the freight rate following a discrete Random Walk. Mossin finds that when there are transaction costs related to laying up and taking the vessel back into trade, the threshold values for entry and exit are respectively higher and lower than under certainty. Dixit & Pindyck (1994) investigate the same problem, but under the assumption that freight rates follow a geometric Brownian motion. Martinussen (1993) and Tvedt (1997) show by numerical examples that the value of the option to lay-up decreases as the remaining lifetime decreases. This is because the probability that the freight rate will fall below the trigger level for lay-up within the remaining time period decreases. This is a general result for the “time value” of options. In practice, the one-year timecharter rate will never be lower than operating costs for the average vessel. Thus, in this particular case, the lay-up option has no value and is ignored for the remainder of the thesis.

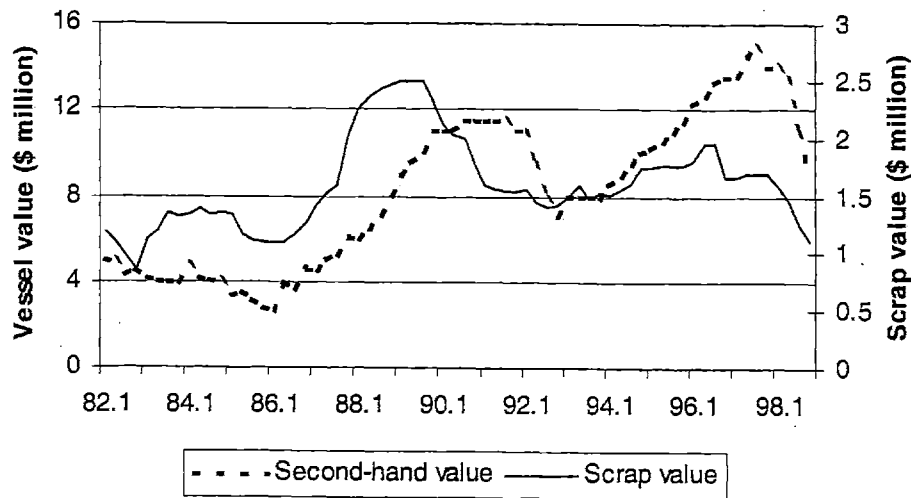
3.3.2 The scrapping option

Shipowners around the globe constantly grapple with the question of whether to further extend a ship's life or sell it for scrap. The decision to continue trading any vessel will be primarily determined by its quality, the costs of life extension, regulatory obsolescence, and the anticipated earnings potential. Another critical factor is the policy of the shipowner towards the ownership and operation of elderly tonnage. Ascertaining precisely when a tanker, or any vessel for that matter, moves from being a moneymaker to a fiscal liability is an inexact science at best. Historically, the large volumes of scrapped ships have occurred after a prolonged period of low freight rates with no immediate prospects of recovery. This is mainly because of decreasing ship values, but also the fact that during recessions, repair and maintenance costs are normally kept at a minimum level, and this neglect may not be retrievable. As a result, the vessel may lose its value as a sales object due to its poor physical condition.

Although the supply of ships for scrapping depends on the state of the freight market, the demand is largely exogenous. The historical development of the value of a 15-year-old product tanker (constant age) and its scrap value is indicated in the figure below.

While good freight markets reduces the supply of scrapping candidates and tend to increase the scrap price, the demand elasticity reduces the correlation to $\rho = 0.48$ in the product tanker market. The correlation between the one-year timecharter rate and the scrap price is 0.30.

Figure 3: Scrap value versus second-hand value



Source: Marsoft Inc

In previous research such as Tvedt (1997), Martinussen (1993), and Stray (1992) it is assumed that the ship owner will scrap the vessel as soon as the value of the ship as a going concern falls below the scrap value. Furthermore, the scrap value of the vessel is treated as constant throughout the lifetime of the ship. While the scrap value certainly is less volatile than the second-hand value, the correlation and volatility may be sufficiently high to introduce second-order effects in the valuation of an old vessel when the second-hand value is approaching the scrap value. When the freight rate is low, not only the vessel value but also the scrap value will tend to be low, making immediate scrapping a less favorable alternative. Let V_t be the value of the vessel and S_t be the scrap value of the vessel. Then the payoff of the scrapping option at the time of exercise is given by $\text{Max}[V_t, S_t]$ where V_t and S_t are stochastic and correlated.

4 Advanced theoretical vessel valuation

4.1 Existing research

4.1.1 Freight rate modeling

In one of the earliest econometric applications, Koopmans (1939) investigated the determinants of tanker freight rates by a model of supply and demand. Since then, a number of empirical analyses of freight rates, e.g. Hawdon (1978), Norman and Wergeland (1981), Stranden (1986) and Beenstock and Vergottis (1993) have built upon these earlier efforts. These studies are basically attempts to model freight rates and other variables of interest together with their determinants in linear regression systems where the equations are solved simultaneously.

A relatively new approach to model freight rates in shipping is using only the freight rates themselves, either in multivariate time series models (e.g. Veenstra & Franses, 1997) or continuous-time stochastic models (e.g. Tvedt 1997, Goncalves 1992). In a stochastic model, the freight rate represented as a continuous-time diffusion process, satisfying a time-homogeneous stochastic differential equation (SDE):

$$dX_t = \mu(X_t)dt + \sigma(X_t)dZ_t$$

Here, Z is a standard Brownian motion, and μ and σ , the drift and diffusion of the process $\{X_t\}$, are functions only of the contemporaneous value of X_t . Many functional forms have been proposed, the main difference being their assumed functional forms for

μ and σ in the equation above. Practitioners often use the Black & Scholes model for valuing simple options on freight rates. The model was originally developed for the pricing of European options on stocks. The increment of the geometric Brownian motion is given by the stochastic differential equation (SDE):

$$dX_t = \mu X_t dt + \sigma X_t dZ_t$$

where μ is the expected rate of growth and σ is the instantaneous standard deviation of the relative change in freight rate. Z_t is a one-dimensional standard Brownian motion, i.e. $dZ_t \sim N[0, dt]$ and $Z_0 = 0$. In this model, the freight rate is log-normally distributed. The advantage of this representation, apart from the availability of analytical results regarding option pricing, is that the freight rate X_t cannot attain negative values, which is also the case in the real world. However, the price process has no mean reverting property, and can thus diverge from reasonable freight levels as time passes. The price for a shipping service is not comparable to the price of a stock, where, in the long term under normal circumstances, value added results in an exponential growth. Capacity adjustments ensure that this is not sustainable in the freight market. Several authors, among them Robert Næss (1990), Alf Andersen (1992), Bjørn Stray (1992) and Jostein Tvedt (1993) have tested the goodness of fit of this stochastic process applied to freight rates. Although the results are inconclusive, most authors reject this representation.

As an alternative, Bjerksund & Ekern (1995) and Tvedt (1997) postulate that the spot freight rate follows an Ornstein-Uhlenbeck process, another well-known stochastic process where analytical results are readily available. Its increment is given by the SDE:

$$dX_t = \kappa \cdot (\alpha - X_t)dt + \sigma \cdot dZ_t$$

The parameter κ governs the degree of mean reversion. The higher κ , the faster the process reverts to its long-term level α . If $X_t > \alpha$ the drift term is negative, and if $X_t < \alpha$ the drift is positive. Thus, the drift term tends to push the process back to its long-term level. The instantaneous standard deviation of the change in the freight rate is given by σ . The freight rates in the Ornstein-Uhlenbeck process are normally distributed around a given mean, and are therefore not downward restricted. In the real world, a negative freight rate will never occur because the shipowner is better off laying up his vessel at rates that do not cover operational costs.

Tvedt (1997) also suggests that the freight rate process be described by a Geometric Mean Reversion (GMR), which has an increment given by:

$$dX_t = \kappa(\alpha - \ln X_t)X_t dt + \sigma \cdot X_t dZ_t$$

where, as before, κ governs the rate of mean reversion, and the logarithm of the freight rate X_t is reverted towards the long-term level α . The GMR process is mean reverting

with zero as an absorbing level since the freight rate is log-normally distributed. In addition, it secures that reversion is strong and volatility is high when rates are high, and vice versa. This is an interesting quality given the fact that rates often stay at a moderate level with low volatility for long periods followed by short periods of high rates and high volatility.

4.1.2 Vessel valuation models

Several theoretical models for the valuation of ships, like any other real assets, have been developed over the years. Beenstock & Vergottis (1993) take the approach that ships are demanded by investors who seek to earn a return on their wealth. Theory suggests that the proportion of wealth that investors wish to hold in an asset depends on the difference between its expected return and the returns on competing investments. The return in shipping consists of profit and capital gains. Capital theory then leads to a suggested equilibrium price.

Tvedt (1997), among others, regards the ship as a risky security that is a claim to the cashflow from ship operation which is derived from the freight rate process. By using "no arbitrage" arguments and the fact that the instantaneous returns on all freight rate dependent contingent claims are perfectly correlated, one can derive a partial differential equation (PDE) that must be satisfied by all freight rate derivatives:

$$\frac{1}{2}\sigma(X)^2V_{xx} + [\mu(X) - \lambda(X)]V_x + V_t - rV + D = 0$$

For the purpose of vessel valuation, the derivative V is the value of the vessel and the «dividend» D is the cash flow from operation. When the vessel reaches the maximum age T or the value as a going concern falls below the scrap value at time τ the vessel is sold for demolition retrieving the scrap value S_τ . The vessel value is equal to the market value of the cash flow generated from time t to τ :

$$V_t = E_t^Q \left[\int_t^\tau e^{-r(s-t)} D_s ds + e^{-r(\tau-t)} S_\tau | \mathcal{F}_t \right]$$

where the expectation is taken under the certainty equivalent martingale measure Q , allowing discounting at the risk free rate r (see e.g. Duffie 1996). As a closed-form solution is not available, a numerical procedure such as the finite difference method has to be used to solve for the value function V_t .

Apart from using parametric models that do not fit well with empirical data, several weaknesses are inherent in existing research. Operating costs are usually treated as constant over time, and Tvedt (1997), among others, does not account for upgrading costs relating to the special and intermediate surveys. It is evident that the upgrading cost can be quite high and is very important for the life extension decision and vessel valuation. Moreover, the authors treat the scrap price as a constant, while, in reality, it is highly volatile and correlated with the vessel value. For a "marginal" old vessel, changes in scrap value and freight rate become important for estimating the remaining lifespan of the vessel and the corresponding present value of future earnings. In a period

of high freight rates and moderate scrap prices, even an old vessel is expected to have many years of remaining operating life, resulting in a high market value. This creates non-linearity in the relationship between market value and freight rates. Other factors such as reduced commercial off-hire (waiting for cargo) in good markets will amplify this tendency.

4.1.3 Non-parametric estimation

A serious problem with any parametric model, particularly when there is no economic reason why we should prefer one functional form to another, is misspecification. Even if a model fits freight rate movements well in sample, this does not necessarily imply that it will price securities well. That is because the price today of a freight rate dependent security, such options of timecharter contracts, depends on the entire distribution of possible future freight rates between today and the future maturity of the security. Fitting historical data well is not a guarantee of matching this entire distribution. Recent research on interest rates has used non-parametric estimation techniques to avoid arbitrary functional forms for the drift μ and diffusion σ . The procedure described below (Stanton 1997) is general and will be used to estimate the freight rate model in this thesis.

Under suitable restrictions on μ , σ and an arbitrary function f , we can write the conditional expectation $E_t[f(X_{t+\Delta}, t)]$ in the form of a Taylor series expansion

$$E_t[f(X_{t+\Delta}, t+\Delta)] = f(X_t, t) + Lf(X_t, t)\Delta + \frac{1}{2}L^2f(X_t, t)\Delta^2 + \dots + \frac{1}{n!}L^n f(X_t, t)\Delta^n + O(\Delta^{n+1})$$

where L is the infinitesimal generator of the process $\{X_t\}$. Ignoring all higher-order terms gives a first-order approximation for Lf :

$$Lf(X_t, t) = \frac{1}{\Delta} E_t[f(X_{t+\Delta}, t+\Delta) - f(X_t, t)] + O(\Delta) \quad (1)$$

To approximate a particular function $g(X_t, t)$, we now merely need to find a function f satisfying $Lf(X_t, t) = g(x, t)$. To derive approximations of the drift, μ , consider the function $f(x, t) \equiv x$. From the definition of L we have $Lf(x, t) = \mu(x)$. Substituting into the equation above leads to a first-order approximation for μ :

$$\mu(X_t) = \frac{1}{\Delta} E_t[X_{t+\Delta} - X_t] + O(\Delta)$$

Similarly, to construct approximations to the diffusion, σ , consider the function $f(x, t) \equiv (x - X_t)^2$. From the definition of L , we have:

$$Lf(x, t) = 2(x - X_t)\mu(x) + \sigma^2(x) \quad \text{and so}$$

$$Lf(X_t, t) = \sigma^2(X_t)$$

Substituting into equation (1) yields a first-order approximation for σ^2 :

$$\sigma^2(X_t) = \frac{1}{\Delta} E_t \left[(X_{t+\Delta} - X_t)^2 \right] + O(\Delta)$$

The higher the order of the approximation, the faster it will converge to the true drift and diffusion of the process when observing the variable X_t at finer and finer time intervals. However, we may only observe X_t relatively infrequently, and we may wish to avoid market microstructures by not sampling too frequently. The empirical results of the non-parametric estimations are presented in the next section.

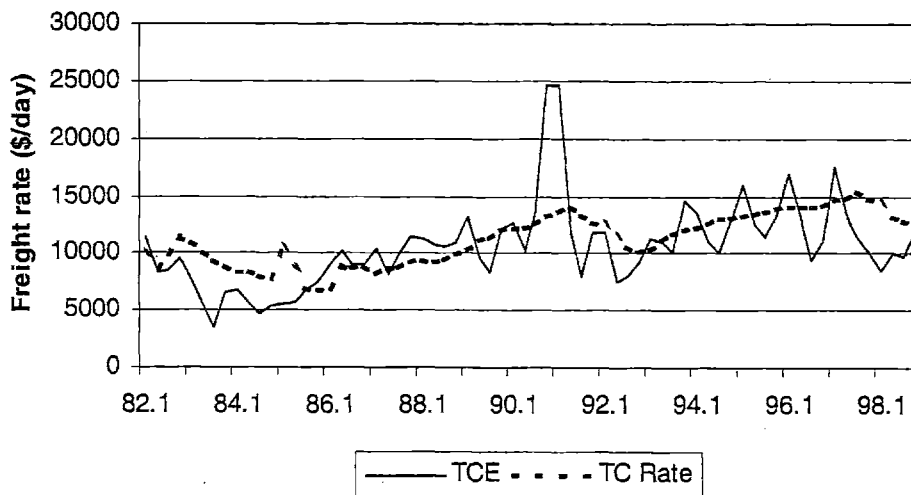
4.2 The freight rate model

4.2.1 The freight rate data

The empirical estimates are based on the one-year timecharter rate for a product tanker in the Caribbean - U.S. trade. The observations are quarterly averages for the period 1982 - 1998. By using a one-year timecharter rate rather than the spot freight rate one avoids the issue of seasonal variations in the tanker markets. Moreover, the one-year timecharter rate is used extensively in the industry as an indicator of the state of the freight market, as the highly volatile spot rate may reflect very short-term supply squeezes in a limited geographical region. The short-term spot freight rate variations resulting from the clearing of cargoes and vessels available in a certain loading area are not necessarily indicative of the longer-term swings in the freight rate. Consequently, the one-year timecharter rate is believed to be a better underlying price process for the

purpose of calculating the vessel value. However, as indicated in Chapter 3, a more advanced valuation model will have to account for the full term structure of freight rates. The figure below shows the historical development of the one-year timecharter rate and includes the spot freight rate (timecharter equivalent, TCE) for comparison.

Figure 4: Historical freight rates for a product tanker



Source: Marsoft

The time-series is positive and seemingly mean-reverting. The average one-year timecharter freight rate over the 18-year period was \$11,692 per day. Notice that these freight rates are quoted for a "representative" vessel built in the 1980's. At a given freight rate level (\$/ton) there will be considerable variations in daily earnings between vessels due to different fuel consumption, cargo carrying capacity, and speed. An important question in this context is whether freight markets differentiate freight rates by vessel age and design. Some practitioners maintain the spot market may prefer a modern ship, but that it will not pay more provided the old ship does the job safely. In

other words, an older tanker may face more idle time. Others say old tankers obtain substantially lower freight rates than modern tonnage, and apply a freight rate deflator of 0.6% to 1.2% per year. This reflects that the shipowner may have to offer commercial discounts in order to find employment. Whether revenue is lost due to waiting or lower freight rate, there will be a negative impact on earnings for an older vessel. As the freight rate model in this thesis is based on freight rate quotes for a vessel built in the early 1980's, any deflationary effect is implicitly taken into account.

4.2.2 Time series stationarity

It is appropriate to test whether the time series of freight rates is stationary. Stationarity implies that the mean and variance are constant over time and that the autocovariances and autocorrelations only depend on the time difference between observations. Consider one version of the Augmented Dickey Fuller (ADF) test for a time series Y_t :

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 t + \sum_{j=1}^p \gamma_j \Delta Y_{t-j} + \varepsilon_t$$

where ε_t is Gaussian white noise. The number of lagged terms p is chosen to ensure the errors are uncorrelated. The null hypothesis is that the time series is non-stationary with a unit root ($\alpha_1 = 0$). The test statistics are easily calculated using statistical software, in this case EVIEWS. Based on the Akaike information criteria the optimal number of lags is two, resulting in the following test statistics:

Table 1: Stationarity test statistics

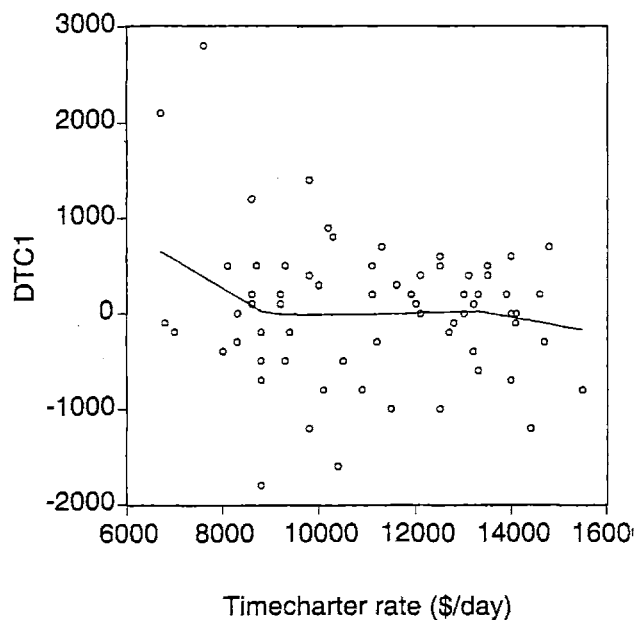
ADF Test Statistic	-2.781138	1% Critical Value*	-4.1035
		5% Critical Value	-3.4790
*MacKinnon critical values for rejection of hypothesis of a unit root.			

The null hypothesis of a unit root is rejected against the one-sided alternative if the t-statistic is less than (lies to the left of) the critical value. The null hypothesis of a unit root cannot be rejected and the time series is said to be non-stationary.

4.2.3 Empirical results

Empirical estimates for the first-order approximations to the drift and diffusion terms outlined in the previous section were obtained using the statistical software Eviews.

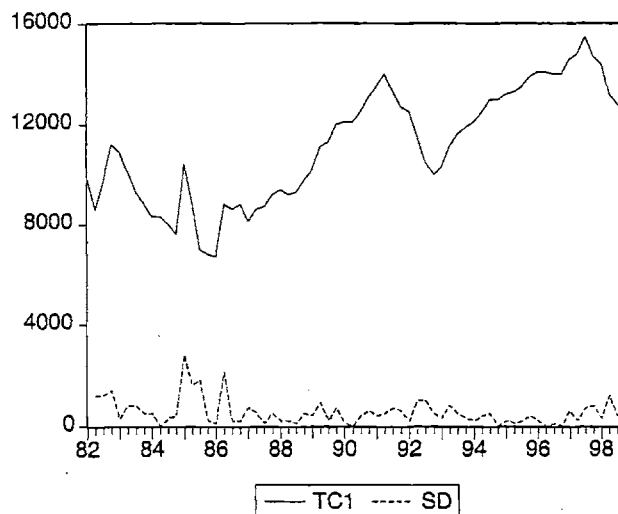
Figure 5: Drift term



The estimated drift provides some support to the existence of mean reversion in freight rates. At low levels (below \$9000/day) the freight rate tend to increase (positive drift), and at high levels (above \$14,000/day) the freight rate tend to decrease (negative drift). At medium freight rate levels the drift is zero, indicating that the freight rate increments are pure noise around a zero mean. In other words, the freight rate follows a Random Walk at medium freight rate levels but tends to revert from extreme levels.

There is no clear relationship between the instantaneous standard deviation of the change in the freight rate (σ) and the freight rate level, as indicated in the figure below.

Figure 6: Historical volatility



If anything, the volatility has decreased since the depressed freight markets in the 1980's. In order to avoid negative timecharter rates in the simulations, it is necessary to impose the restriction that the volatility approaches zero when the freight rate

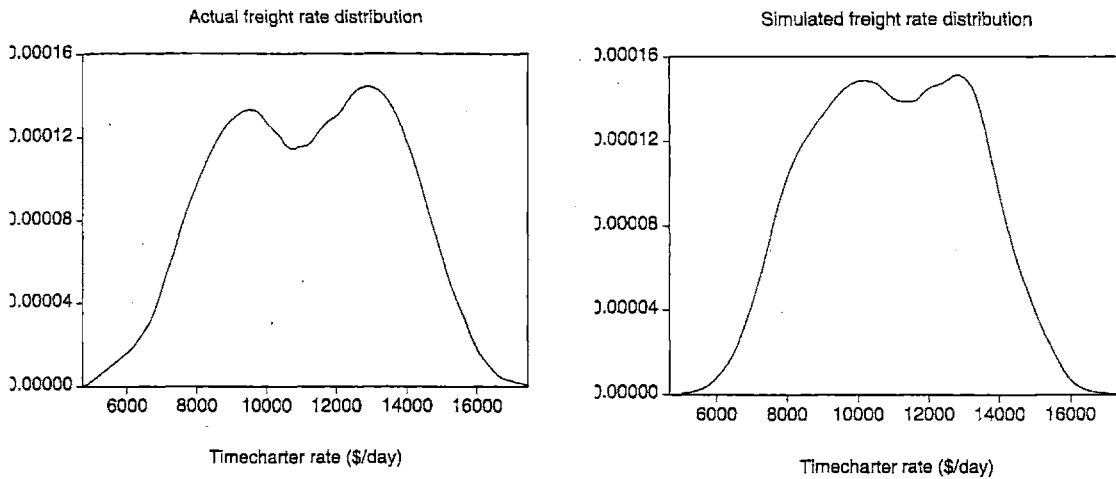
approaches zero. However, for the purpose of simplicity the volatility is assumed to be constant and equal to the arithmetic average since 1987, or $\sigma = 600$. The strong upward drift built into the model at low freight rates precludes simulated freight rates below \$4,500 per day. Using the non-parametric estimates for the drift $\mu(X)$ and diffusion σ , the discrete-time freight rate model is given by:

$$X_t = X_{t-1} + \mu(X_{t-1}) + \sigma \cdot Z_{1,t}$$

where $Z_{1,t} \sim N(0,1)$.

The figure below compares the historical density distribution of freight rates with the simulated distribution (10,000 data points) using the simple freight rate model above.

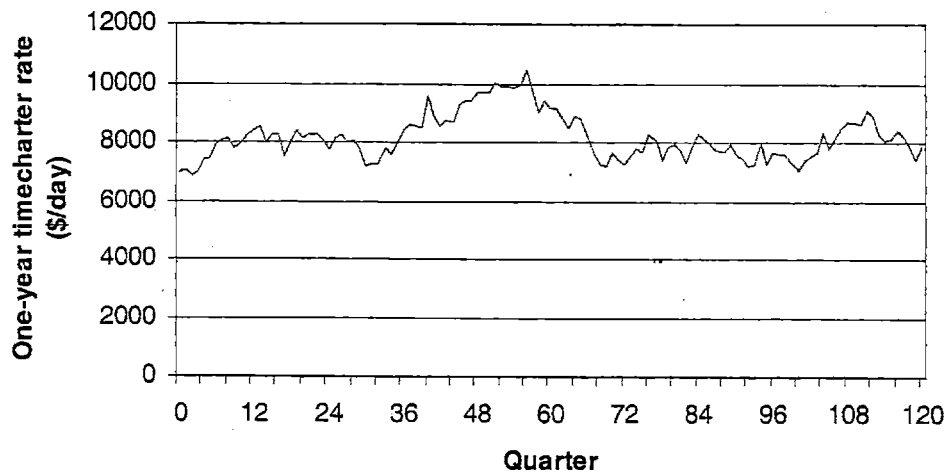
Figure 7: Comparison of historical and simulated freight rate density distributions



The simulated distribution is very close to the actual distribution, indicating that the freight rate model is a good approximation to the real stochastic behavior of freight

rates. The bi-modality is an interesting feature in both distributions, and may be a result of the combination of mean reversion from extreme freight rate levels and a random walk. An example of the simulated timecharter freight rate path resulting from the discrete-time model above is shown in the figure below.

Figure 8: Example of simulated freight rate path

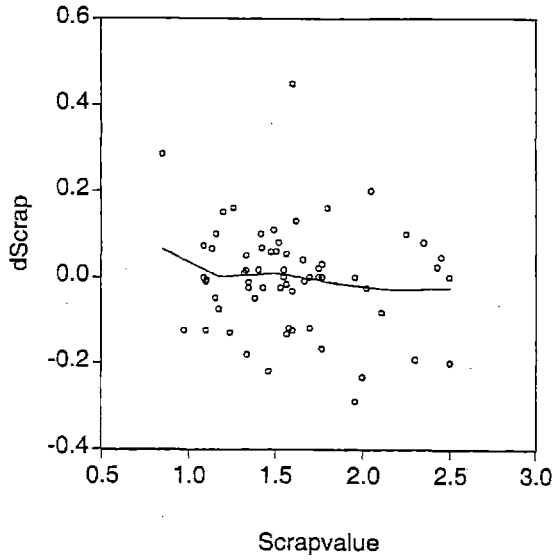


4.3 The scrap price model

The scrap value also shows weak mean reversion as indicated in the figure below.

Although the statistical evidence for mean reversion is weak, the scrap value has historically fluctuated between a lower limit of about \$800,000 and an upper limit of about \$2.5 million for this vessel type, corresponding to a scrap price between \$80 and \$250 per lightweight ton.

Figure 9: Estimated drift of scrap value $\mu(S)$



Again, there is no clear relationship between the scrap value and the instantaneous standard deviation of the change in the scrap value (σ). Consequently, the volatility is taken as constant and equal to the average standard deviation over the full time period, $\sigma = 0.083$. The discrete-time stochastic process for the scrap value is given by:

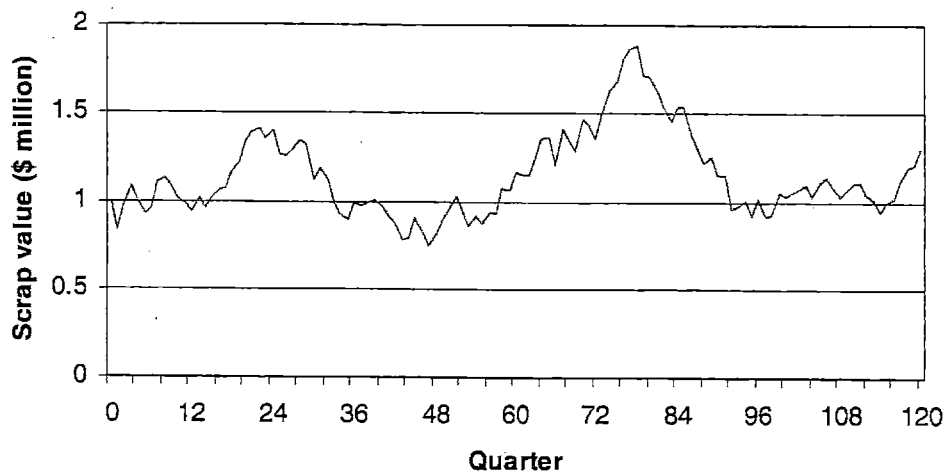
$$S_t = S_{t-1} + \mu(S_{t-1}) + \sigma \cdot Z_{2,t}$$

where, as before, Z_2 is $N(0,1)$. However, the stochastic increment Z_2 is also correlated with the stochastic increment for the freight rate Z_1 . There is a straightforward method to simulate two normally distributed variables that are correlated. Suppose ε_1 and ε_2 are independent and distributed $N(0,1)$. Let $Z_1 = \varepsilon_1$ and

$$Z_2 = \rho \cdot \varepsilon_1 + \varepsilon_2 \sqrt{1 - \rho^2}$$

Then $\text{corr}(Z_1, Z_2) = \rho$ and both are distributed $N(0,1)$. An example of the simulated scrap price process is shown in the figure below.

Figure 10: Example of simulated scrap value path



4.4 Additional assumptions

4.4.1 The market price of risk

Knowing the process governing movements in a state variable such as the freight rate is not enough to allow us to price contingent claims whose payoffs depend on that variable. The contingent claims may be ship values, forward freight agreements, or options on these assets. In general, when an underlying variable is the price of a traded security, the risk neutral valuation shows that investor attitudes to risk are irrelevant to the relationship between the price of a derivative and value of the underlying variable.

However, the freight rate is not a traded security, and to price freight rate dependent assets we need to know the market price of risk $\lambda(X_t, t)$. Previous authors have assumed various functional forms for λ in the tanker freight markets. For instance, Tvedt (1997) assumes risk neutrality, or $\lambda = 0$. To my knowledge, few recent studies have investigated the risk attitude of the market players and the resulting market price of risk from an empirical view in the tanker market. An empirical study on the tanker market from 1967 to 1976 presented by Norman (1981) suggests that there exists a risk premium, i.e. that the tanker operators are rewarded with higher rate of return when operating in the highly volatile spot market compared to short- or long-term time-charters. Lorange & Norman (1971) present the result from a panel study of the risk attitude of Norwegian ship owners. The results imply that the majority of the players are risk-prone or risk-neutral when their liquidity is good, and risk-averse otherwise. Unfortunately, estimating the market price of risk is difficult due to the lack of a standardized and liquid market for tanker freight rate derivatives. As the historical average return on capital in the product tanker market is only 4.0% p.a., assuming a risk-neutral world in which assets earn the risk-free rate seems reasonable. Consequently, in this thesis, it is assumed that the market price of freight rate risk is zero.

4.4.2 The interest rate process

Although the risk-free interest rate is a stochastic variable, the LIBOR is considered to be deterministic and constant at 7% for all maturities. An improved model will have to account for the uncertainty in the term structure of interest rates. I hope to return to this subject in the research for my doctoral thesis.

4.4.3 Operating costs

The daily operating cost for a vessel will generally increase as time goes by due to aging and general price inflation. These issues were treated in depth in section 3.2.1. For a product tanker that is five to nine years old, Drewry Shipping Consultants estimates the following daily operating cost:

Table 2: Daily operating costs (fixed age)

Year	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
\$/day	5,305	5,655	6,005	5,970	5,585	5,380	5,490	5,580	5,715	5,930

Price inflation was only 1% p.a. on average over this ten-year period. In fact, there were some years with deflation. In addition there will be some cost escalation due to the aging of a vessel. Unless otherwise noted the operating cost for a new vessel is assumed to be \$5,500/day, increasing by 1.4% per year.

4.5 Monte Carlo simulation

The embedded real options (lay-up and scrapping) and the correlated stochastic processes for the freight rate and scrap price introduce a complexity that make an analytic solution to the valuation problem impossible and valuation using a binomial tree/finite difference method approach difficult. Rather than relying on traditional parametric freight rate models and PDEs that have to be solved numerically, the vessel value in this thesis is calculated using Monte Carlo simulation. The general idea is that

even if you cannot find a solution for the value of an asset, you can simulate its payoff under different scenarios, repeat the simulation many times, and then compute recursively what the asset should be worth. This calculation is performed under the risk-neutral distribution, meaning that all assets are assumed to earn the risk free rate and that the discount rate equals the risk-free interest rate.

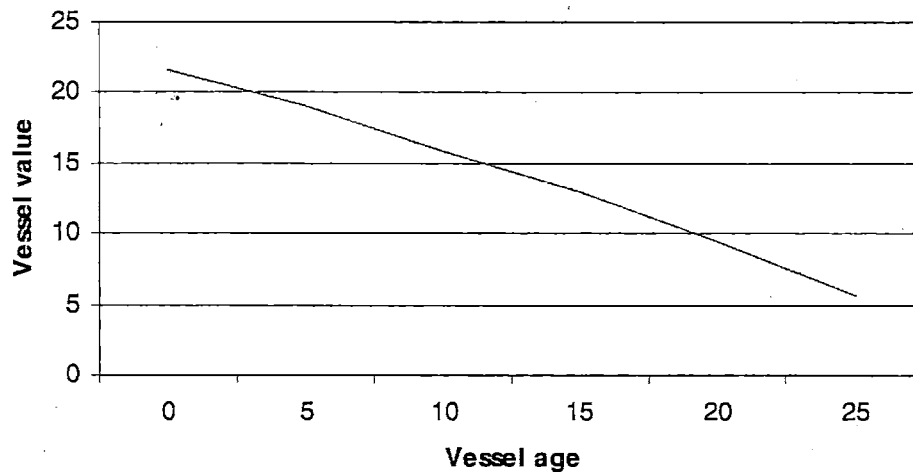
In order to calculate the value of a vessel, 2000 sample paths are calculated for the scrap price and the freight rate, using their respective stochastic price processes that were developed in the previous sections. A time series of freight rate/scrap value pairs constitutes one trial. For every trial, the vessel value is then calculated recursively (starting at the end) as the present value of the quarterly operating profits in the remaining lifespan plus the discounted future scrap value. If the scrap value at a given point in time exceeds the expected vessel value as a going concern, the vessel is assumed to be scrapped, and its value is reset to the prevailing scrap value. The present vessel value is calculated as the arithmetic average of the values from each trial. Note that the standard error of this estimate is inversely proportional with the square root of the number of trials.

5 Empirical results

5.1 The theoretical depreciation curve

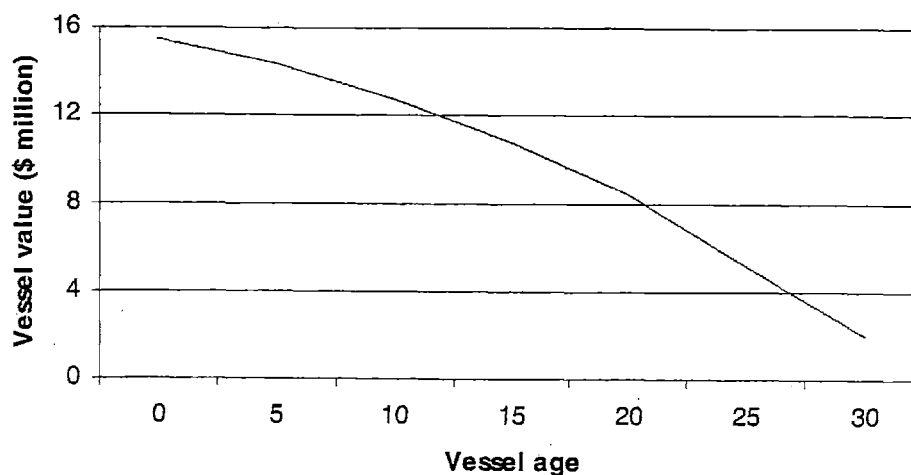
The Monte Carlo procedure can be used to develop a theoretical depreciation curve simply by changing the age of the vessel and keeping all other input parameters constant. The result is shown in the figure below for a current freight rate of \$11,000/day.

Figure 11: Theoretical depreciation curve, moderate freight rate



At least for moderate freight rate levels, the results confirm that the industry standard of straight-line depreciation is a good approximation to the actual reduction in vessel value as ships age. However, some practitioners maintain that vessels depreciate differently in different markets. Consider the case of a low current freight rate of \$7,000/day, which results in a theoretical depreciation curve as shown below.

Figure 12: Theoretical depreciation curve, low freight rate

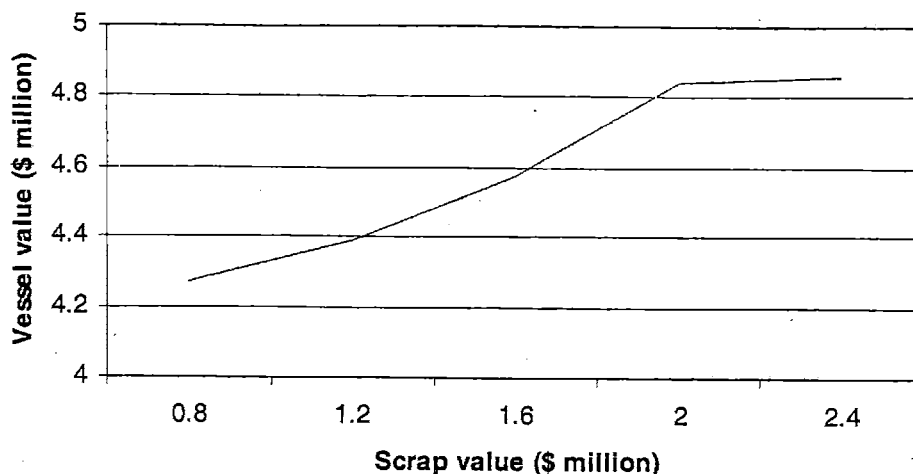


The relationship in this case is slightly non-linear. The reason is presumably that for an old vessel, the probability that the freight rate will recover within the remaining lifetime is small, leading to accelerated depreciation. There are indications that depreciating a vessel over a period as short as 15 - 20 years will underestimate the economic value of an older vessel. The life expectancy for 1970's-built tankers have changed from maybe 15 - 20 years in the 1980's to 25 - 30 years at present. The theoretical model indicates that depreciation over 30 years in fact would be more appropriate for valuation purposes.

5.2 Sensitivity analysis

It is likely that the prevailing scrap value will have an impact on the valuation of an old vessel. The figure below illustrates this point for a 25-year-old vessel at a current freight rate of \$10,000/day.

Figure 13: The impact of scrap value

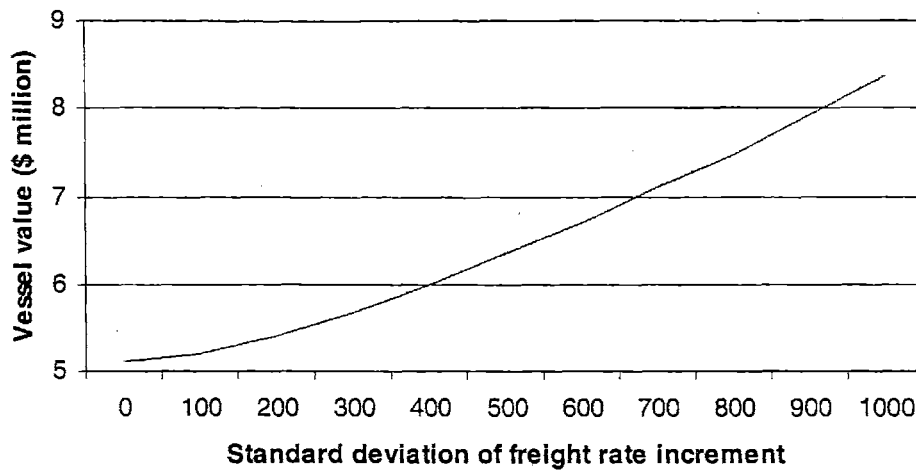


As the vessel still has a few years of remaining trading life at these freight rate levels, an increase in the current scrap value will not result in an equal increase in vessel value.

An increase in scrap value of \$1 million increases the vessel value by approximately \$0.5 million in this case. However, a very high scrap value will not persist due to the mean reversion in scrap prices, and has little or no impact on valuation. The kink in the graph is due to the low number of data points.

While the instantaneous rate of change (standard deviation) of the freight rate is assumed to be constant and equal to 600 in this thesis, it is likely that the volatility has a big impact on the vessel value, as is the case for most derivatives. The figure below illustrates this point for a 20-year old vessel at a freight rate of \$9,000/day.

Figure 14: The impact of volatility

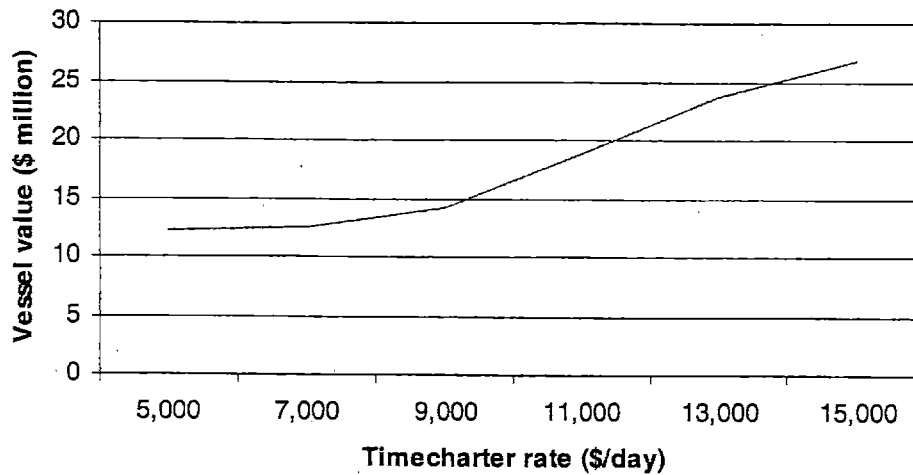


Higher freight rate volatility increases the vessel value. This is because the mean reversion is stronger at low freight rate levels than at high freight rate levels, so higher volatility tends to increase the average freight rate. The importance of volatility suggests that the assumption in this thesis that volatility is constant over time introduces pricing errors. Future revisions of this work should incorporate a volatility model.

5.3 Comparison with market data

By holding all input parameters except the freight rate constant one can compare the results with actual market data as depicted in Figure 1. For a five-year old vessel, the model results in the following relationship:

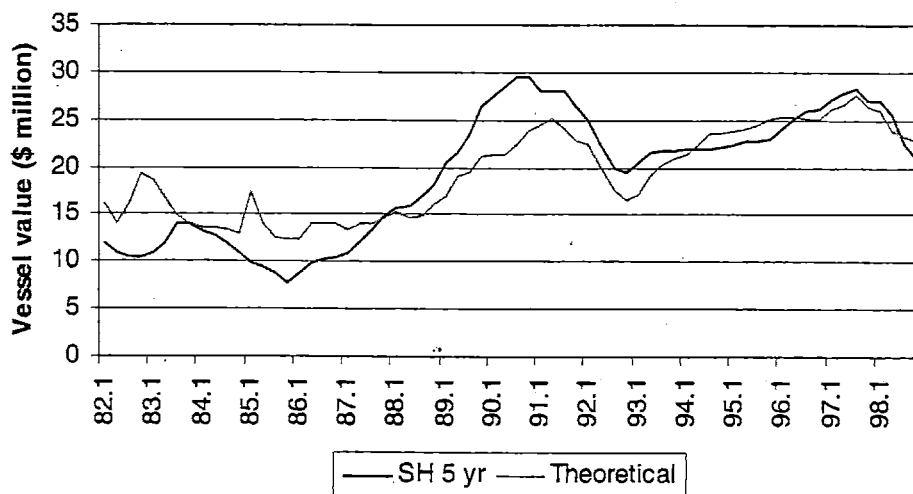
Figure 15: Timecharter rate and theoretical vessel value



The relationship is not linear. The major reason is the mean reversion that is built into the theoretical freight rate process. In other words, low freight rates will not persist for long but will tend to drift towards moderate levels (\$9,000/day - \$14,000/day). This places a floor on the vessel value. Similarly, the mean reversion at high freight rates means the vessel are not valued as if the high freight rates will persist, but rather from knowing that "all good things must come to an end". This is especially true in the bulk shipping markets, where periods of high freight rates tend to be short lived. When comparing with Figure 1 it is interesting to note that the theoretical valuation model is consistent with actual market data for medium freight rates. For instance, at a timecharter rate of \$10,000/day, the historical market price for a five-year old vessel was \$17 million, compared to \$16.6 million according to the theoretical model. This is a surprisingly good result. On the other hand, market values are seemingly too low at low freight rates (below \$9,000 per day) compared to the model, and too high at very high freight rates. This is again due to the mean-reversion effect. The market seems to

believe that very low and very high freight rates will persist and price the vessels accordingly. For easier comparison, the figure below shows the time series of vessel values compared to calculated vessel values according to the theoretical model.

Figure 16: Theoretical vs. market values

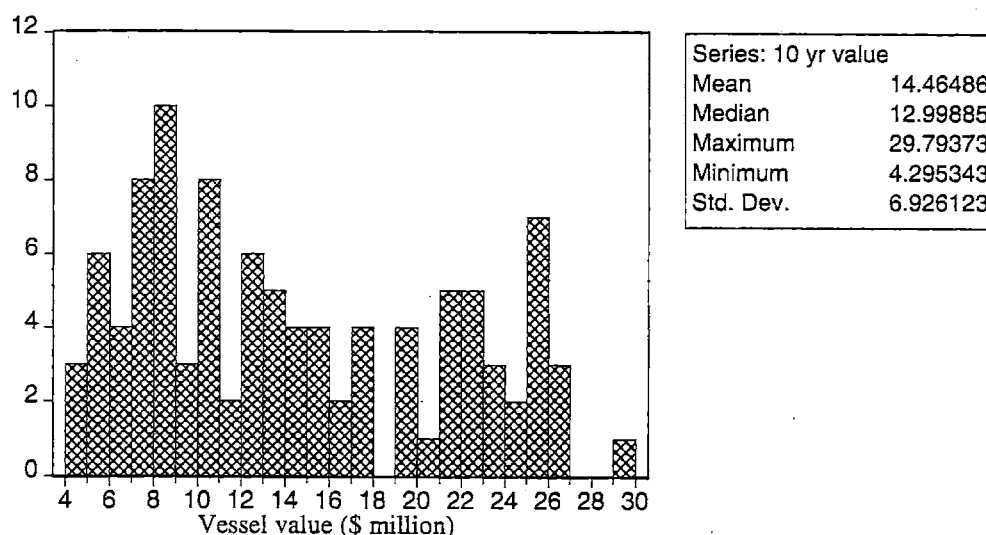


If one believes in the theoretical pricing model, the market seemed undervalued in the early and mid 1980's and overvalued in the early 1990's. After 1994, a 10-year old product tanker has been "correctly" priced. However, there are several potential sources of errors in the theoretical model. Firstly, the assumption that the discount rate is constant and equal to a low 7% p.a. is dubious. Secondly, even though investors appear risk neutral in cross-sectional data, it is possible that they require a higher risk premium in periods of low freight rates and a lower risk premium in times of high freight rates. Such a time-varying risk premium could easily remove any "mispricing". Until these extensions have been incorporated, and the model calibrated further, the figure above should hardly be used for investment decisions.

5.4 Other applications

A successfully calibrated and computationally efficient theoretical vessel valuation model allows for a number of interesting applications. One application is to forecast the distribution of residual values. For instance, consider the case where a shipping bank is considering lending money to a shipowner to buy a five-year-old vessel that currently sells for \$17 million. It is of interest for both parties to know what the vessel may sell for at the end of the holding period, say five years from now. A by-product of the Monte Carlo simulation is the distribution of possible future vessel values in five years, as shown in the figure below. More simulations will give a smoother distribution.

Figure 17: The distribution of residual values



The bank can use this distribution for risk management calculations such as computing the default risk or the necessary collateral. The shipowner can calculate the range of possible holding-period returns. Note that this approach does not require the forecasting of freight rates, an exercise that has a very poor track record beyond one year.

There are also a number of advanced applications in the derivatives market. For instance, a financial institution can issue a put option to a shipowner, giving him the right to sell his vessel at a predetermined price, say \$8 million in five years. By using the distribution of future vessel values and discounting the option payoff ($\text{Max}[\$8\text{m} - \text{vessel value}, 0]$) to the present, the fair value of this option can be calculated as the average of the NPVs. In this particular case, the shipowner would have to pay \$0.30 million today for the right to sell his vessel for no less than \$8 million in five years.

6 Asset play

6.1 Introduction

Based on the preliminary results in the previous chapter, it is not evident that asset play - constantly buying and selling vessels for profit - will be profitable based solely on fundamental analysis. In this context, the fundamental value of the vessel is its theoretical value based on simulations of future earnings. Instead, in this chapter, the profitability of using technical analysis for asset play is investigated. Technical analysis is a generic term that includes many different techniques with the goal of predicting the future evolution of asset prices from the observation of past prices. These techniques are considered by many to be the original form of investment analysis dating back to the writings of Wall Street Journal editor Charles Dow in the 1800s, long before modern financial theory was born. Most of the time, technical analysis has been looked at with contempt by academics. The main reason is that technical analysis violates the efficient market hypothesis which holds that it is impossible to predict future prices from the

observation of past prices. Furthermore, early tests of the profitability of technical trading rules produced very poor results, which reinforced the negative attitude in academia towards such analysis. However, practitioners are still using these techniques to make investment decisions. Over the last decade, a number of empirical studies have produced results on the predictability of asset prices that seemingly contradict the efficient market hypothesis, and, over the same time period, there has been a renewed interest in technical analysis also from an academic point of view. By and large, recent academic literature suggests that technical trading rules are capable of producing valuable economic signals. The results are in sharp contrast with most of the earlier studies that supported the random walk hypothesis and concluded that the predictable variation in returns was economically and statistically very small. Two competing explanations for the presence of predictable variation in asset prices have been suggested: (1) the markets are not efficient even in the weak form, or (2) markets are efficient and the predictable variation can be explained by time-varying risk premiums.

This approach in this thesis is in line with recent literature on technical trading rules which tests whether such rules are profitable when the results are adjusted for transaction costs and the potential effect of data snooping. Despite the intriguing qualities of second-hand bulk vessel markets, such as large long-run price swings exhibiting a clear mean reverting pattern, there have been no recent attempts to investigate the merits of asset play models in this context. The reason, aside from being a less-known market, may be that financial markets dealing in stocks and foreign exchange provide easily accessible and long time series of standardized high-frequency

data, while the shipping markets do not. Also, most practitioners regard technical analysis as a short-horizon trading method, with positions in the stock, commodity or foreign exchange markets lasting a few hours or days. When an investor buys a ship, the transaction itself may take several weeks. However, there are indications that, in a cyclical market such as bulk shipping, technical analysis may be a tool to uncover market turns. Vessel values may not always be determined by economic fundamentals like freight rates, but rather driven away from fundamental values by shipowners' irrational expectations of future freight rates. Returns in the second-hand market for ships typically exhibit the characteristics that Cutler, Poterba and Summers (1990) suggest are typical to speculative dynamics: (1) returns display positive autocorrelations at relative short horizons, (2) returns are negatively autocorrelated at durations of several years, and (3) returns over periods of several years can be predicted on the basis of crude proxies for the deviation of asset prices from fundamental value. A proxy for the fundamental value in this case could be a multiple of earnings. Stopford (1997) estimates that when freight rates are high, the S & P market values a five-year old ship at about six times its annual earnings. In recessions, the value may fall as low as three times annual earnings.

6.2 Previous research

Technical trading rules investigated in academic literature can be divided in two major areas: filter rules and moving average rules. Early research, such as Alexander (1961 and 1964) focused on filter rules to assess the efficiency of stock price movements. In his first article Alexander found the filter rules to be profitable. However, after he

included transaction costs in his second article, the profits generated by these strategies vanished. Fama and Blume (1966) confirmed this conclusion and this led the academic community to be skeptical about technical analysis not only because it lacked theoretical foundation but also because it yielded poor results. Sweeney (1988) re-examined the results of Fama and Blume for a subsequent time period and found that, depending on the level of transaction costs, filter rules still yielded profitable results.

In the early nineties, the research focused on moving average crossover rules, which are some of the most popular and common trading rules discussed in the technical analysis literature. Brock, Lakonishok and LeBaron (BLL 1992) investigated moving average rules on daily data of the Dow Jones Industrial Index from 1897 to 1986 and concluded that the buy and sell signals generated by these rules were able to detect "abnormal" returns. By using bootstrap tests, BLL showed that the results were robust to other specifications of the return generating process. However, BLL ignored trading costs. Furthermore, Sullivan, Timmerman and White (STW 1998) show that BLLs "best" trading rule did not outperform the buy-and-hold benchmark at conventional levels of significance in the ten-year period that followed. Hudson, Dempsey and Keasey (1996), who replicate the Brock et al's tests on the UK stock market for the period 1935 to 1994, found that any profitable results vanished when trading costs were considered. Isakov and Hollistein (1997) confirm the same result in Swiss stock prices for the period 1969 to 1997. Levich and Thomas (1993) and Kho (1996) found some profitable results with the moving average strategies in the foreign exchange futures markets, even after accounting for transaction costs. Kho showed that these results were partly due to a

time-varying risk premium. Evidence in favor of technical analysis is also reported in Osler and Chang (1995) who use bootstrap procedures to examine charting pattern in foreign exchange markets.

The only previous research I have come across that attempts to use technical trading rules on second-hand vessel values is Norman (1981). Based on a simple AR(1) model of the asset price and the empirical frequency distribution of prices, Norman derives a trading rule that generates a buy signal whenever the vessel value falls below a certain threshold and a sell signal when the value rises above the same threshold. Norman reports a return on capital of 15.6% for the optimal threshold, corresponding to being in the market 84% of the time. However, he does not report the return on capital from a benchmark buy-and-hold strategy. Marcus et al (1991) develops an investment strategy based on the deviation in vessel value from the fundamental value (nominal production cost). Although their approach is based on the observed cyclical nature of the bulk shipping markets, the authors introduce exogenous variables, and, accordingly, their work can not be considered as strictly technical analysis.

6.3 Data snooping

An important issue generally encountered, but rarely directly addressed when evaluating technical trading rules, is data snooping. Data snooping occurs when a given set of data is used more than once for purposes of inference or model selection. The potential impact of data snooping on the performance of technical trading rules was recognized early on by Jensen and Bennington (1970) who refer to it as a "selection bias". Data

snooping can be a result of a particular researcher's efforts, or it can result from a subtle survivorship bias operating on the entire universe of technical trading rules. Rules that happen to perform well historically receive more attention, and if enough parameterizations are considered over time, some rules are bound by pure luck to produce superior performance even if they do not genuinely have predictive power. Negative results are ignored, while positive results are published and taken to indicate that trading rules can yield profits. For example, there is a vast literature on pricing anomalies in the equity markets, summarized by Ball (1995) and Fortune (1991). Roll (1994) finds that these aberrations are difficult to exploit in practice, and suggests that they may be partially the result of data mining. Lo and MacKinlay (1990) try to quantify the effects of data snooping in financial asset pricing models. Although technical analysis has not been used extensively by researchers or investors in the bulk shipping markets, the adoption of well-known trading rules from the stock and foreign exchange markets may introduce exactly the same selection bias in this case. In addition, the selection of the "best" trading rule from a large universe of rules and parameterizations is a data mining exercise in itself.

Previous research (e.g. BLL 1992) has evaluated the statistical significance of the findings by fitting several models to the raw data and re-sampling the residuals to create numerous bootstrap samples. The bootstrap approach introduced by Efron (1979) is not new to the evaluation of technical analysis. The idea is to check if the technical trading rules are robust to other specification of the return generating process by calculating p-values from a simulated empirical distribution. Isakov and Hollistein (1998)

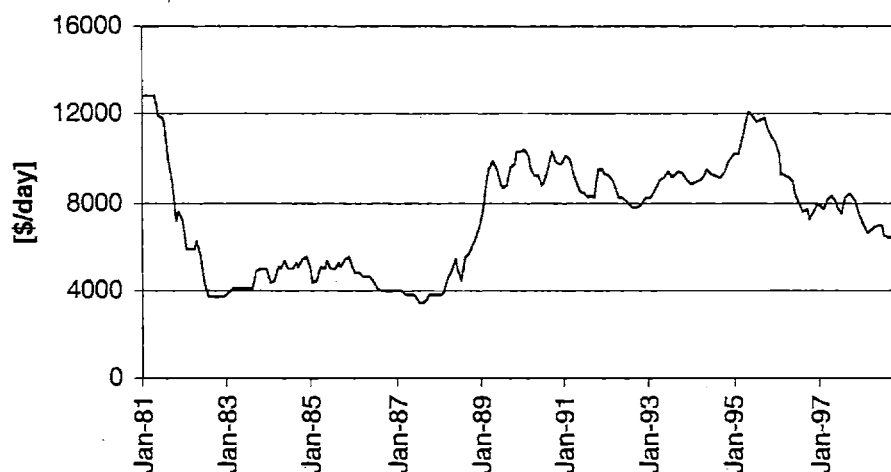
acknowledge that the predictability of asset returns could be due to some well-known features of the data such as non-normality, serial correlation and time-varying moments, and perform bootstrap tests to check if these features bias the test statistics. Assuming that the returns follow an AR(1) and a GARCH(1,1) process, their results indicate that, although the features are present in the data, they are not the cause of profitability (in the absence of trading costs) of the technical trading rules.

As acknowledged by BLL (1992), such bootstrap tests are not able to compute a comprehensive test across all rules, as such a test would have to account for dependencies between results for different trading rules. They try to mitigate this problem: (1) by reporting results from all their trading strategies, (2) by using a very long data series, and (3) emphasizing the robustness of results across non-overlapping sub-periods for statistical inference. As an alternative, Lo and MacKinlay (1990) recommend a ten-year out-of-sample performance experiment as a way of purging the effects of data-snooping biases from the analysis. Similarly, as a solution to the data-mining problem, Neely, Weller and Dittmar (1997) apply genetic programming techniques to the foreign exchange market. Genetic programming is a method by which a computer searches through the space of technical trading rules to find a group of rules that generate positive excess returns. These good rules are then tested on out-of-sample data to see if they continue to generate positive returns. STW (1998) adopt a modified "Reality Check Bootstrap" introduced by White (1997) that provides a procedure to test whether a given model has predictive superiority over a benchmark model after accounting for the effects of data-snooping. The approach of STW is adopted here.

6.4 Data description

The data in this chapter on asset play are monthly rather than quarterly as vessel values can change quickly, with monthly holding period returns as high as 90%. Factors such as the relatively large trading cost² and the required time to complete a transaction prohibit trading on short-term (weekly) signals. Monthly shipbroker estimates of freight rates and vessel values for a Product tanker between January 1981 and December 1998 are illustrated below. The data set consists of $n = 216$ observations.

Figure 18: Monthly one-year timecharter freight rates



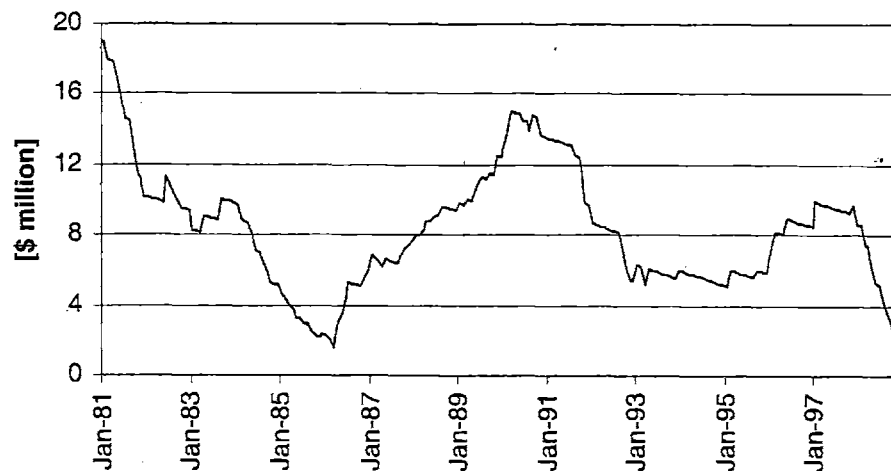
Source: Fearnleys AS, Oslo, Norway

The daily operating profit is calculated by subtracting the daily operating costs from the timecharter freight rate. For simplicity, the operating cost has been fixed at \$5,500/day

² The trading cost consists of a commission to the shipbroker, typically 1% of the vessel value and paid by the seller, as well as any costs of transferring the ownership.

in this chapter. Again, the effect of lay-up as a measure to limit losses at low freight rates is ignored. For the buy-and-hold strategy, it is assumed that the vessel is bought five years old in the beginning of 1981 for \$19 million and that its book value is linearly depreciated to scrap value (approx. \$1 million) over the last 18 years, corresponding to \$1 million annually. The resulting price development is illustrated in the figure below.

Figure 19: Vessel value 1976-built product carrier



Source: derived from Fearnleys AS, Oslo, Norway

In the subsequent sections, the trading signals are generated on the basis of vessel values alone, although it can be argued that the technical trading rules should be assessed on the basis of a price series that incorporates the information inherent in the freight rate series. However, operating profits are included when calculating the returns from the technical trading rules. The monthly returns for the buy-and-hold strategy are illustrated below.

Figure 20: Period returns (monthly)

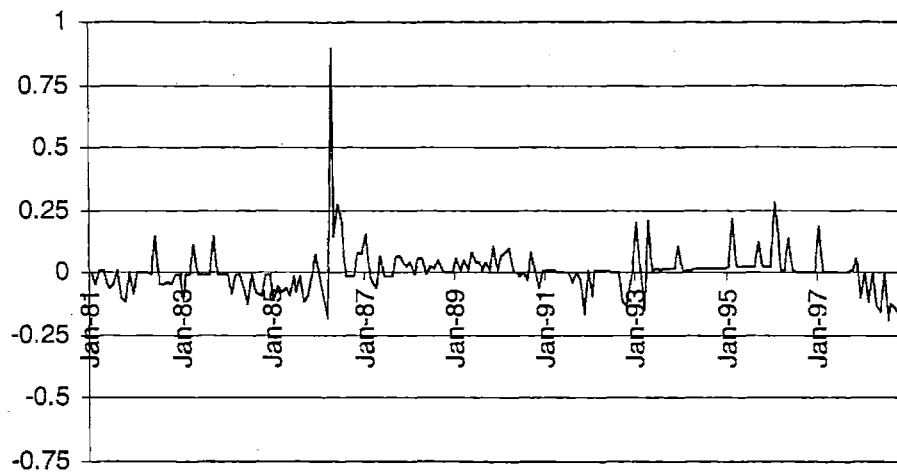


Table 3: Summary statistics for monthly returns of the buy-and-hold strategy

Mean	0.003244
Standard Error	0.007006
Standard Deviation	0.102963
Kurtosis	29.90262
Skewness	2.535463
Minimum	-0.54724
Maximum	0.900613
$\rho(1)$	0.225*
$\rho(2)$	0.213*
$\rho(3)$	0.185*
$\rho(4)$	0.163*
$\rho(5)$	0.154*

*Significant at the 5% level for a two tailed test

The average monthly return for the buy-and-hold strategy corresponds to 4.0% annually, which is less than the risk-free interest rate during the time period. This is typical in the shipping industry as investors seem to be attracted by the potential for large short-term profits rather than a decent long-term return. The figures in Table 3 show that the return series is asymmetric as indicated by the positive skewness coefficient and that it is leptokurtic, i.e. it has fatter tails than the normal distribution. There is also a significant positive short-term autocorrelation in the monthly returns up to the fifth order.

6.5 Methodology

6.5.1 The universe of trading rules

As technical analysis is not widely used in the shipping industry, it is necessary to specify an appropriate universe of trading rules based on previous academic studies of financial markets and the technical analysis literature. As the application of technical analysis to this market is a new approach, the parameterizations (ref. Appendix A) of the large number (1053) of technical trading rules are chosen more or less arbitrarily. The focus in this chapter is on filter rules, support and resistance levels, and moving averages, the principles of which are described below.

Filter rules

Fama and Blume (1966) explain the x percent filter rule as follows: "If the daily closing price of a particular security moves up at least x per cent, buy and hold the security until its price moves down at least x per cent from a subsequent high, at which time

simultaneously sell and go short. The short position is maintained until the daily closing price rises at least x per cent above a subsequent low at which one covers and buys. Moves less than x per cent in either direction are ignored." A subsequent high is interpreted as the highest closing price achieved while owning a vessel. Likewise, a subsequent low is the lowest closing price achieved while being out of the market.

Moving averages

The standard moving average (MA) cross-over rule generates a buy (sell) signal when the asset price penetrates the MA from below (above). Hence, a long position is retained as long as the price trend remains above the MA, alternatively, as long as a fast MA remains above a slow MA, where the slow MA is calculated over a greater number of months. Two types of filters may be imposed to filter out false (loss-making) trading signals. The fixed percentage band filter requires that the difference between the slow MA and the fast MA exceeds $b\%$ of the slow MA in order to execute a buy or sell signal. The introduction of a band reduces the number of "whiplash" buy and sell signals when the short and long-term moving averages are close. The time delay filter requires that the signal remain valid for a certain number of months.

Support and resistance levels

A simple trading rule based on the notion of support and resistance levels is to buy when the closing price exceeds the maximum price over the previous n months, and sell when the closing price is less than the minimum price over the previous n months. A fixed percentage band filter, b , and a time delay filter, c , may be applied as well.

6.5.2 Performance measure

The test procedure is based on the $l \times 1$ performance statistic:

$$\bar{f} = n^{-1} \sum_{t=R}^T \hat{f}_{t+1}$$

Where l is the number of technical trading rules, n is the number of prediction periods indexed from R through T so that $T = R + n - 1$, and $f_{t+1} = f(\beta_t)$ is the observed performance measure for period $t + 1$. In this application $n = 198$ and $R = 18$, accommodating technical trading rules that need 18 months of data in order to produce a trading signal. The various parameterizations of the trading rules ($\beta_k, k = 1, \dots, l$) generates the returns that are used to calculate the performance measure. The form for $f_{k, t+1}$ is adjusted slightly compared to previous literature (e.g. STW 1998) to account for the period vessel operating profits (Z_t) during a long position:

$$f_{k, t+1} = \ln[1 + y_{t+1} S_k(\chi_t, \beta_k)] - \ln[1 + y_{t+1} S_0(\chi_t, \beta_0)] \quad k = 1, \dots, l$$

Where

$$\chi_t = \{X_{t-i}\}_{i=0}^R$$

X_t is the price series of vessel values, $y_{t+1} = (X_{t+1} + Z_t - X_t)/X_t$, and $S_k(\cdot)$ and $S_0(\cdot)$ are signal functions that convert the sequence of price index information χ_t into market positions. $S_k = 1$ represents a long position (own the vessel) and $S_k = 0$ represents a neutral position (out of the market). In other words, we assume that short selling (selling a vessel one does not own) is not possible. The lack of a maritime derivatives market would have prevented a synthetic replication of short sales. However, another

way to achieve similar results is to use the following strategy: when an investor observes a buy signal he borrows half of the vessel value. This yields twice the market return less the borrowing rate. When the investor observes a sell signal, he sells the vessel and invests all his money in a risk-free asset. If the frequency and duration of long and neutral (sell) positions is similar and the borrowing rate is close to the lending rate such a strategy would yield similar results to a long-short strategy. This is also a strategy that is used by most shipowners, as very few use only owners' equity for vessel purchases. However, this approach is not implemented here, which means the calculated mean returns from the use of the trading rules are conservative.

The natural null hypothesis is that the performance of the best technical trading rule is no better than the performance of the benchmark buy-and-hold position. Thus, if f_k is the excess return over the benchmark strategy corresponding to trading rule k :

$$H_0 : \max_{k=1, \dots, J} \{E(f_k)\} \leq 0$$

Rejection of this null hypothesis indicates that the best trading rule achieves performance superior to the benchmark. It is assumed throughout the study that an investor in a neutral position obtains a risk-free interest rate equal to *zero* on his accumulated wealth. In order to replicate real trading conditions, a transaction cost of 1% of the vessel value is subtracted at the time of a sale. Moreover, in a low-volume market such as the second-hand sale & purchase market for ships one may experience problems similar to non-synchronous trading effects in the financial markets, as a

shipowner is not likely to be able to purchase or sell a vessel on short notice. There simply may not be a suitable vessel for sale at the time of a "buy" signal, or an interested buyer at the time of a "sell" signal. Alternatively, the pre-purchase activities such as the inspection of a potential vessel and the price negotiation may take several weeks. To address this issue, a trading signal observed in month t can be implemented in month $t+1$. This issue is not explicitly treated here. However, the empirical results indicate that the introduction of a time delay in the execution of a buy or sell signal generally has a negative effect on the returns of a technical trading rule.

White (1997) shows that H_0 can be evaluated using the stationary bootstrap of Politis and Romano (1994) to the observed value of $f_{k,t}$. Following the notation of STW (1998), resampling the returns from the trading rules yields B bootstrapped values of f_k , denoted as $f_{k,i}^*$, where i indexes the B bootstrap samples. Consider the statistics

$$\bar{V}_l = \max_{k=1,\dots,l} \left\{ \sqrt{n} \left(\bar{f}_k \right) \right\},$$

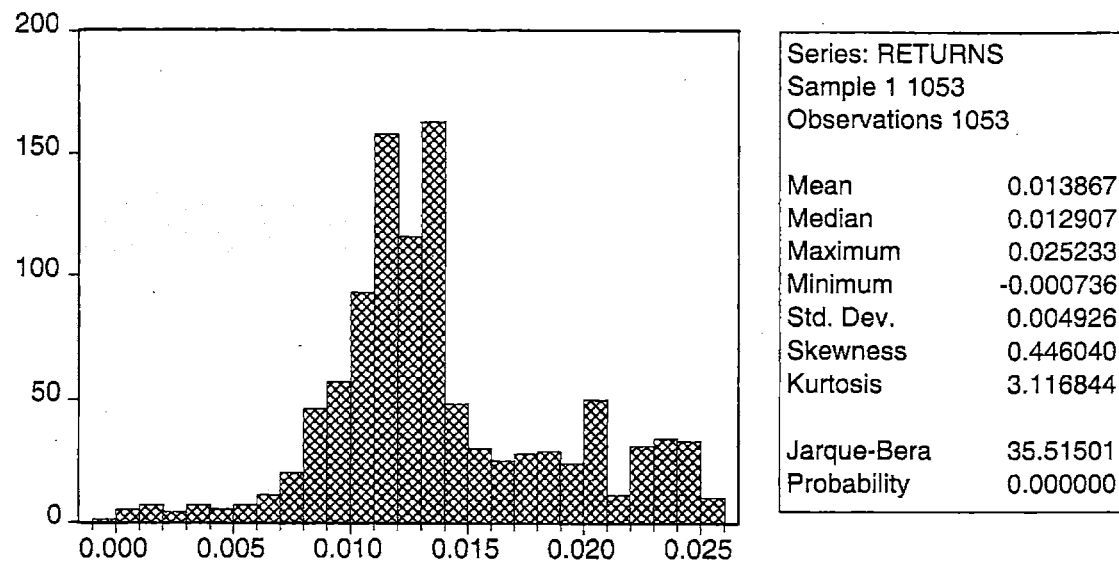
$$\bar{V}_{l,i}^* = \max_{k=1,\dots,l} \left\{ \sqrt{n} \left(\bar{f}_{k,i}^* - \bar{f}_k \right) \right\}, i = 1, \dots, B$$

By comparing V_l to the quintiles of $V_{l,i}$ one obtains White's Reality Check p value for the null hypothesis. By employing the maximum value over all the l trading rules, the p value incorporates the effects of data-snooping from the search over the l rules.

6.6 Empirical results

At first sight, the performance of the technical trading rules seems very convincing. Out of all the 1053 parameterizations, only ONE trading rule results in a negative mean return f_k compared to the benchmark buy-and-hold strategy. Moreover, none of the trading rules results in a negative net cumulative wealth, even when accounting for trading costs. The net cumulative wealth is calculated as the sum of all trading profits/losses, both from vessel operation and asset play. Unfortunately, the data set is not large enough to permit a meaningful out-of-sample experiment. The figure below presents the histogram of mean returns:

Figure 21: Frequency distribution of monthly trading rule returns



Due to the apparent superior performance of many of the 1053 trading rules considered, the consideration of dependencies between trading rules (data snooping effects) is unlikely to overturn a conclusion that the best-performing trading rule outperforms the buy-and-hold strategy. In the 18-year period from 1981 to 1998 the best-performing trading rule according to the mean return criterion is a filter rule with an average annualized excess return of 34.9% p.a. compared to the return from the buy-and-hold strategy. The corresponding net profit over the full time period is \$23.84 million, or \$23.35 million after trading costs.

Note that the best-performing trading rule according to the mean return criterion is not necessarily the parameterization that results in the highest cumulative net wealth. When the investor is long the excess return is zero, as the benchmark is the buy-and-hold strategy. Consequently, this criterion favors trading rules that are better at predicting downturns in the market (when the excess return is positive) and not up-turns which is when the investor will actually make money given that short sales are not possible. Due to the small number of trades, the trading costs have little impact in this market.

The table below reports the statistics for the best-performing trading rule according to the mean return criterion. Note that the mean returns for the long and neutral positions in Table 4 are absolute returns rather than excess returns compared to the buy-and-hold strategy.

Table 4: Best-performing trading rule according to mean return criterion

Description	N(long)	N(neutral)	#trades	$\mu(\text{long})$ [σ]	$\mu(\text{neutral})$ [σ]
Filter rule	121	77	7	0.028993 [0.06171]	-0.03175 [0.144272]

N(long) and N(neutral) are the number of months an investor is long or neutral respectively. $\mu(\text{long})$ and $\mu(\text{neutral})$ reports the mean monthly return obtained in long or neutral positions, with the sample standard deviation in brackets.

According to the best trading rule, the investor would have been in the market 61% of the time and made seven trades (buy + sell). The table indicates that the trading rule is capable of identifying market trends, as the mean return in long positions is positive (40.9% p.a.) while the mean return in neutral positions is negative (-45.5% p.a.). In terms of volatility, returns associated with long positions have a lower standard deviation than returns associated with neutral positions. This is consistent with a well-known feature of asset returns called the leverage effect and initially documented by Black (1976). Moreover, an investor who used the best trading rule for asset play would have obtained returns (in long positions) that are higher than the returns of the buy-and-hold strategy and yet have lower standard deviation (ref. Table 4). From a risk-reward point of view, this observation supports the notion that the best technical trading rule outperforms the benchmark buy-and-hold strategy.

Assume for a moment that the distribution of returns in this market is normal, stationary and time-independent so that the standard t-ratio tests are applicable. The corresponding

t-statistic to test the null hypothesis that the buy/sell mean return according to the best trading rule is equal to the buy-and-hold strategy is given by (BLL 1992):

$$t = \frac{\mu_r - \mu}{\left(\frac{\sigma^2}{n} + \frac{\sigma^2}{n_r} \right)}$$

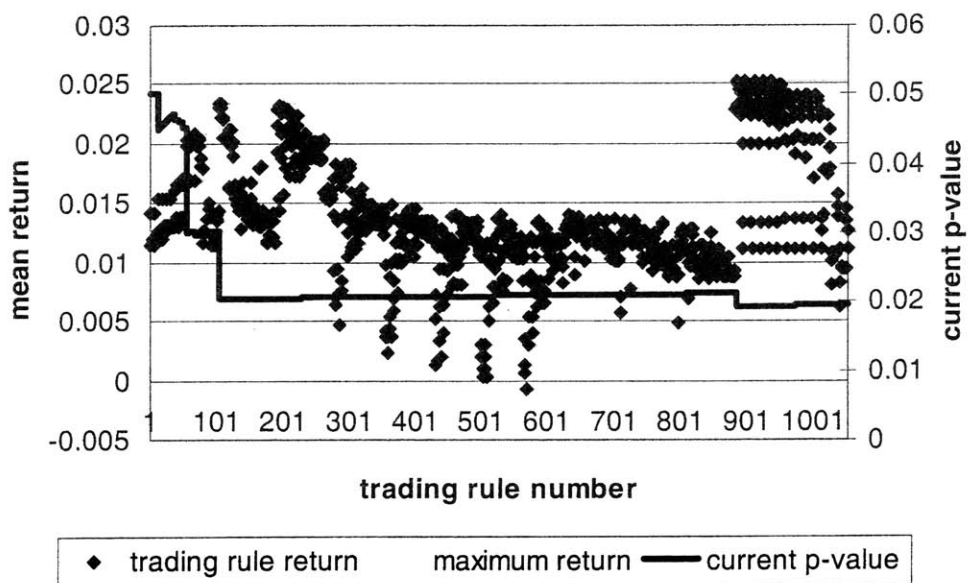
where μ_r and n_r are the mean return and total duration of the long/neutral positions, and μ and n are the unconditional return from the buy-and-hold strategy and the total number of observations. σ^2 is the estimated variance for the entire sample. The resulting t-statistics are 2.17 and -2.53 for the long and neutral positions respectively. Hence, the mean returns obtained by using the trading rule are statistically different from the return of the buy-and-hold strategy at the standard 5% level of significance. Of course, the returns do not satisfy the assumptions behind these calculations. Nevertheless, these results support the notion that the best-performing technical trading rule outperforms the benchmark.

The results so far are intriguing but it remains to be seen whether the results stand up to an adjustment for data-snooping/data-mining effects. After all, the best trading rule is drawn from a large universe of parameterizations. Following STW (1998), two possible outcomes can occur when an additional trading rule is inspected. If the marginal trading rule does not lead to improvement over the previously best-performing trading rule, the p-value for the null hypothesis that the best model does not outperform will increase, effectively accounting for the fact that the best trading rule has been selected from a

larger set of rules. On the other hand, if the marginal trading rule improves on the maximum performance statistics, then this can reduce the p-value since better performance increases the probability that the optimal model genuinely contains valuable economic information.

The figure below illustrates the sequential development in maximum mean return performance and p-value for the null-hypothesis as more trading rules are considered. The data-snooping adjusted p-value is calculated according to White's Reality Check as explained in section 6.6 with $B = 500$ bootstrap samples.

Figure 22: Economic and statistical performance of the best rule



The figure plots each trading rule against its mean return (measured on the left y-axis). The upper line tracks the highest mean return up to and including a given number of trading rules (indicated on the x-axis). The lower line indicates the bootstrapped p-value (right y-axis). The maximum mean return starts out around 0.014 (16% p.a.) and quickly increases to 0.023 (32% p.a.), yielding a p-value of 0.02 after the first 120 trading rules have been considered. After approximately 900 trading rules have been considered, the best performance is improved to the final 0.025 (35% p.a.) and the p-value is kept to a level of less than 0.02. Ultimately, the only numbers that matter are those at the extreme right of the graph, as the order of experiments is arbitrary. Note that what appears to be vertical clusters of mean return points simply reflect the performance of neighbor trading rules in a similar class as the parameters of the trading rules are varied.

7 Conclusions and discussion

7.1 Theoretical vessel valuation

The theoretical vessel valuation model developed in this thesis is the first step in a promising new line of research in maritime economics. As there are numerous possibilities for improvement and further calibration with real life data, the results can not yet challenge the existing valuation methods in bulk shipping. However, there are indications that vessels have occasionally been incorrectly priced in the past when compared to its fundamental value. While the results confirm that straight-line depreciation is a good approximation to the actual reduction in vessel value as ships age,

there is a question whether the time period over which the vessel is depreciated for valuation purposes should be higher than the typical 15 - 20 years. The results also indicate that scrap values and, in particular, freight rate volatility are important input parameters in the valuation of a vessel.

Apart from the obvious simplifications that have been made, such as constant discount rate and freight rate volatility, it is always appropriate to be suspicious towards empirical models that are only tested in sample. That is, the results are compared with the data that are the basis for the estimation in the first place. This could partly explain the good fit with vessel values in the late 1990's and the poor fit with previous vessel values. Clearly, the vessel values in the 1980's were based on the experience and data up to that point in time. It is therefore not appropriate to say that the market was inefficient just because it does not fit with the theoretical model. The ultimate test for any empirical model is how well it performs out of sample. Another caveat that has already been mentioned is the possible presence of time-varying risk-premiums required by investors.

7.2 Asset play

The findings in this thesis support a conclusion that technical analysis and asset play can be used to achieve far better returns than the long-term operation of a ship. The best-performing technical trading rule is capable of outperforming the benchmark by an astounding 35% per year. Moreover, none of the trading rules generate negative cumulative wealth, and only one parameterization results in a mean return that is lower than the return from the benchmark buy-and-hold strategy. The results for the best-

performing trading rule show that the mean return following buy signals is positive and the mean return following sell signals is negative, both significantly different from the buy-and-hold mean return according to standard statistical tests. Moreover, the returns following buy signals are less volatile than those following sell signals, as well as the returns of the buy-and-hold strategy. Of course, there is no guarantee that this apparent superior performance will continue in the future, and the ultimate test of the best-performing trading rule would be an out-of-sample test after another ten years of data. A further issue at stake is how an investor could have possibly determined the best trading rule prior to committing money to a given rule. Admittedly, there is no indication that it would be possible to find *ex ante* the trading rule that will perform the best in the future, and the probability that an investor would pick a trading rule with an excess mean return that is statistically significant is rather small.

Consequently, whether the results have implications for weak form market efficiency is a very subjective topic. In general, two competing explanations for the presence of predictable variations in asset returns have been suggested: (1) market inefficiency in which prices take swings from their fundamental values, and (2) markets are efficient and the predictable variation can be explained by time-varying equilibrium returns. There is little evidence so far that unambiguously distinguishes these two competing hypotheses. STW(1998) argues that the existence of outperforming trading rules would only seem to have implications for weak form market efficiency or variations in the *ex ante* risk premium if the rules under consideration are known during the sample period. The application of technical trading rules to maritime financial data series has hardly

received any attention from researchers, and it is questionable whether the market players in the industry are sophisticated enough to utilize such investing tools. On the other hand, the types of trading rules considered would have been well known from other financial applications throughout the time period.

The main problem is most likely the small size of the market in terms of number of vessels in any given category, and the resulting low liquidity of the sale & purchase market. In other words, there may not be a vessel for sale when the technical trading rule generates a buy signal or a buyer when the trading rule generates a sell signal. Such practical issues may make implementation difficult and reduce the effective returns generated by any trading rule. Although trading costs have been treated in this chapter, the effects of an illiquid market have not been fully considered. The introduction of a time delay in some of the trading rule parameterizations indicates that a delay in the execution of a buy or sell signal has a negative effect on returns. A thorough treatment of this issue in a future edition may overturn the conclusion in this thesis.

8 Future work

While the use of non-parametrically estimated stochastic models is common when modeling interest rates and valuing fixed-income securities, the proposed methodology in this thesis is the start of a new and promising line of research in maritime economics. The stochastic behavior of freight rates and its implications for valuation of freight rate contingent claims, as well as investment and operating decisions, constitute an important

area that should be developed further. Important extensions to the work in this thesis are described in the following sections.

8.1 The term structure of freight rates

Spot freight rates exhibit different stochastic characteristics than long-term timecharter rates. Long-term timecharter rates tend to be less volatile than short-term timecharter rates, and the industry view that operating vessels in the timecharter market is less risky than employing them on a spot basis has been supported by empirical research (Glen & Martin, 1998). This is a necessary result of the mean reversion in spot freight rates. Moreover, since the value of a vessel must be the same whether it is operating in the spot market or in the timecharter market, the risk-adjusted return must be the same across the term structure. If this is not the case, there is room for systematic "arbitrage" such as a shipoperator achieving excess risk-adjusted returns from chartering a vessel on long-term contract and re-letting it in the spot market. In a perfectly competitive market where owners are free to choose between any trading option, such an excess return is not consistent with an efficient market. However, imperfections may arise if the market for either spot trading or timecharters is thin. The research in this area of maritime economics is thin and, to a certain extent, outdated.

Previous research on the term structure of freight rates includes Zannetos (1966), who introduced the importance of expectations in the formation of freight rates. He argues that when the spot rate is below the long-run marginal cost of vessel operation, the timecharter rate will tend to be higher the longer the duration of the contract. Strandenes

(1984) introduces semi-rational expectations into the "term structure" hypothesis. Under this assumption the shipowners are supposed to know the long-term equilibrium of the spot rate but are unfamiliar with the path of convergence. Hale & Vanags (1989) test the expectation hypothesis in the dry bulk markets, which is rejected by the majority of their tests. The timecharter rates follow spot rates more closely than the expectation hypothesis suggests, systematically over-estimating future spot rates in good markets. Veenstra (1999) tests a form of the liquidity preference model in the dry-cargo markets, using Schiller's (1987) net present value model. Veenstra argues that market participants prefer spot contracts and require a liquidity premium to enter timecharter contracts, where the premium is constant over time. The formal rejection of the NPV relation raises significantly doubt concerning the validity of these underlying assumptions. However, Veenstra concludes that the spread between spot and long-term timecharters is an important information variable in shipping. As the standard term structure models have been rejected, there is a clear need to further investigate the stochastic behavior of the term structure of freight rates and the associated structure of risk premiums.

8.2 A two-factor stochastic freight rate model

There are indications that the slope of the term structure as measured by the spread, i.e. the difference between the spot freight rate and, for example, the five-year timecharter rate³ is an important variable. If this is the case, the volatility of the freight rate in the present one-factor model that only accounts for the freight rate level may be severely

³ The timecharter rate, similar to the long-term spot interest rate, can have 1 month to 20 years maturity.

misestimated, as it represents an average across all possible term structures. This could have consequences for the valuation of freight rate contingent claims. As the term structure of freight rates embeds both expectations about future freight rates as well as the risk premium on timecharters of different duration, a two-factor model would shed some light on the structure of term premiums. Moreover, such a two-factor model would provide insights into the importance of volatility for the pricing of freight rate-dependent securities and to which degree the volatility depends on the level and slope of the term structure. Future work should incorporate a two-factor (level and spread) non-parametric model of freight rates along the lines of Stanton et al's (1998) work on interest rates. To have any practical value, the Monte Carlo simulations of such a model must be calibrated to fit the prevailing term structure of freight rates. It is also necessary to develop empirical estimates of the market price of freight rate risk, a subject that has been all but ignored in the existing research.

8.3 The valuation of freight rate contingent claims

In order to better evaluate market efficiency and the potential for asset play based on fundamental values, a more advanced valuation model must be calibrated to actual market data. By developing a model that is consistent with the empirical term structure of freight rates and accounts for varying volatility, stochastic interest rates and the market price of risk, the goal is to find theoretical vessel values that are closer to the observed market values. The non-parametric representation of the underlying freight rate lends itself to a Monte Carlo simulation approach for valuing other freight rate contingent claims such as a call option on a vessel, or an option to extend a vessel timecharter. Such derivatives are sometimes negotiated as a part of a contract between two industry players who usually have no idea what the economic value is and

sometimes gives the option away to sweeten a deal. There is a large need to develop useful valuation models for such over-the-counter options.

8.4 Market efficiency and asset play

It is likely that the observed market values will differ from the values calculated using any theoretical model. However, this does not necessarily mean that the second-hand market for bulk vessels is inefficient and has a lucrative potential for asset play.

Believers in the efficient market hypothesis will argue that any deviations are due to time-varying risk premiums where shipping investors demand a higher expected return in order to buy a vessel when the freight markets are depressed, and a lower expected return when the market is peaking. Another important issue is the informational role of the spot rate versus long-term timecharter rates. Norman (1979) argues that shipowners are too strongly influenced by current spot rates in their assessments of future market conditions, and that this is the reason why owners are seemingly irrational in their contracting decisions. It is important to keep in mind that the spot market is a clearance market for vessels and cargoes immediately available in a small geographical area. Thus, the spot freight rate contains a set of information that may be very different from the information contained in the timecharter rates and asset prices. This issue should be revisited, as the structure of the markets has changed considerably since the 1970's.

9 Bibliography

Alexander, S. (1961): "Price movements in speculative markets: Trends or random walks", *Industrial Management Review* 2, 7 - 26.

Alexander, S. (1964): "Price movements in speculative markets: Trends or random walks, no 2", in P. Cootner, ed.: *The Random Character of Stock Market Prices*, MIT Press, Cambridge, Mass.

Andersen, A. (1992): «Valuation of shipping options», Working Paper no. 14, Foundation for Research in Economics and Business administration (SNF), Bergen.

Beenstock and Vergottis (1993): "Econometric Modelling of World Shipping", Chapman & Hall, London.

Bjerk Sund, P., and Ekern S. (1995): «Contingent claims evaluation for mean reverting cash flows in shipping». In «Real options in Capital investment, Models, Strategies and Applications», edited by L. Trigeorgis (Westport Connecticut: Praeger).

Black, F. (1976): "Studies of stock price volatility changes", *Proceedings of the American Statistical Association*, 177 - 181.

Ball, Ray (1995): "the theory of Stock market efficiency: Accomplishments and Limitations", *Journal of Applied Corporate Finance*, 4 - 17.

Brock, William, Josef Lakonishok, and Blake LeBaron (1992): "Simple technical trading rules and the stochastic properties of stock returns", *Journal of Finance* 47, 1731-1764.

Cutler, David, James M. Poterba and Lawrence Summers (1990): "Speculative Dynamics and the Role of Feedback traders", AEA Proceedings and papers, Vol. 80, No. 2, 63 - 68.

Dixit, A & Pindyck, R. S. (1994): «Investment under uncertainty», Princeton NJ: Princeton University Press.

Duffie, Darrell (1996): «Dynamic asset pricing theory», Princeton, N.J.

Efron, Bradley (1979): "Bootstrap methods: Another look at the jackknife", Annals of Statistics 7, 1 - 26.

Fama E. F. and Blume, Marshall (1966): "Filter rules and stock market trading profits", Journal of Business 39, 226 - 241.

Fortune, Peter (1991): "Stock market efficiency: an autopsy?", New England Economic Review, Federal Reserve Bank of Boston, 18-40.

Glen, D.R. & Martin, B.T. (1998): "Conditional modeling of tanker market risk using route specific freight rates", Maritime Policy & Management, Vol 25, No 2, pp 117-128, Taylor & Francis Ltd. London

Goncalves (1992): "Optimal chartering and investment", unpublished Ph.D. thesis, MIT Ocean Engineering.

Hale & Vanags (1989): "Spot and period rates in the dry bulk market", Journal of Transport Economics and Policy, September, London.

Hawdon, D. (1978): «Tanker freight rates in the short and the long run», Applied Economics 10, 203-217.

Hudson, R., Dempsey M, and K. Keasey (1996): "A note on the weak form efficiency of capital markets: The application of simple technical trading rules to UK stock prices - 1935 to 1994, *Journal of Banking and Finance* 20, 1121 - 1132.

Isakov, D. and Hollistein, M (1998): "Application of simple technical trading rules to Swiss stock prices, Is it profitable?", Research paper No 2, FAME, Geneva Switzerland.

Jensen, Michael and George A. Bennington (1970): "Random walks and technical theories, Some additional evidence", *Journal of Finance* 25, 469-482.

Koopmans, Tjalling C (1939): «Tanker freight rates and Tankship building», Harlem, Netherlands.

Kho, B. C. (1996): "Time-varying risk premia, volatility, and technical trading rule profits: Evidence from foreign currency futures markets", *Journal of Financial Economics* 41, 249-290.

Levich, Richard and Lee, Thomas (1993): "The significance of technical trading rule profits in the foreign exchange market: a bootstrap approach", *Journal of International Money and Finance* 12, 451-474.

Lo, Andrew W. and Craig MacKinlay (1990): "Data-snooping biases in tests of financial asset pricing models", *The Review of Financial Studies* 3, 431-467.

Lorange, Peter & Norman, Victor D. (1973): «Risk preferences in Scandinavian shipping», *Applied Economics* 1973, volume 5, pp. 49-59.

Marcus, H.S., Glucksman, M, Ziogas, B, and Meyer, Karl (1991): "A buy-low, sell-high investment methodology: The case of Bulk Shipping", *Interfaces* 21, 8 - 21.

Martinussen, E. A. (1993): «The importance of scrapping and lay-up for the valuation of VLCCs», unpublished HAS thesis, NHH, Bergen.

Mossin, Jan (1968): «An optimal policy for lay-up decisions», Swedish Journal of Economics 70, pp. 170-177.

Norman, V. (1979): "Economics of bulk shipping", Institute for shipping research, Bergen, Norway

Norman, Victor (1981): "Market strategies in bulk shipping", working paper, Norwegian School of Economics and Business Administration, Bergen, Norway.

Norman, V., and Wergeland, T. (1981): Nortank. A simulation Model of the Freight Market for Large Tankers. Report No. 4. Norwegian School of Economics and Business Administration, Bergen.

Neely, C., Paul Weller, and Robert Dittmar (1997): "Is technical analysis profitable in the foreign exchange market? A genetic programming approach", Journal of Financial and Quantitative Analysis.

Næss, R. (1990): «Beslutninger om opplag eller drift av skip ved usikre rater», unpublished HAS thesis, Norwegian School of Economics and Business Administration (NHH), Bergen.

Osler, Carol and Kevin Chang (1995): "Head and shoulders: Not just a flaky pattern", Federal Reserve Bank of New York Staff Report 4, 1 - 65.

Politis, Dimitris and Joseph Romano (1994): "The stationary bootstrap", Journal of the American Statistical Association 89, 1303 - 1313.

Roll, Richard (1994): "What every CFO should know about scientific progress in financial economics: what is known and what remains to be resolved", *Financial Management*, 69-75.

Schiller & Campbell (1987): "Cointegration and tests of present value models", *Journal of Political Economy*, Vol 95, pp. 1062 - 1088.

Stanton, Richard (1997): «A Nonparametric Model of Term Structure Dynamics and the Market Price of Interest Rate Risk», *Journal of Finance*.

Stanton, Richardson, Boudoukh, and Whitelaw (1998): "The Stochastic Behavior of Interest Rates: Implications from a Multifactor, Nonlinear Continuous-time Model", *Stern School of Business, NY*.

Stopford, Martin (1997): "Maritime Economics", Second edition, *Routledge, London*.

Strandenes, Siri (1984): "World Market Prospects". *Center for applied Research, Norwegian School of Economics and Business Administration, Bergen*

Strandenes, S., P. (1986): «Norship - A simulation model for Bulk Shipping Markets». *World market prospects report no. 6. Norwegian School of Economics and Business Administration, Centre for Applied Research, Bergen, Norway*.

Stray, B. (1992): «Option valuation of securities in the market for very large crude carriers», *Working Paper no. 13, SNF, Bergen*.

Sullivan, Ryan, Allan Timmermann, and Halbert White (1998): "Data-snooping, Technical Trading Rule Performance, and the Bootstrap", *working paper UCSD, Journal of Finance, October 1999*.

Sweeney, Richard (1988): "Some new filter rule tests: Methods and results", *Journal of Financial and Quantitative Analysis* 23, 285-300.

Tvedt, Jostein (1993): «Freight Rates and Asset Valuation», unpublished HAS thesis, NHH, Bergen.

Tvedt, Jostein (1997): «Valuation of VLCCs under income uncertainty». *Maritime Policy and Management*, Vol. 24, No. 2, pp. 159-174.

Veenstra, A. W. (1999): "The term structure of ocean freight rates", *Maritime Policy and Management*, Vol 26, No 3, pp 279 - 293.

Veenstra & Franses (1997): «A Co-integration Approach to Forecasting Freight Rates in the Dry Bulk Shipping sector». *Transportation Research*, Vol. 31, pp. 447 - 458.

White, Halbert (1997): "A reality check for data snooping", technical report, NRDA, San Diego, CA.

Zannetos, Zenon S. (1966): "The theory of Oil Tankship Rates", The MIT Press, Cambridge, MA

10 Appendix A: Trading rule parameters

This appendix describes the 1053 parameterizations of trading rules.

A.1 Filter rules

x = change in security price ($X \times \text{price}$) required to initiate a position

y = change in security price required to liquidate a position

$x, y = 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.10, 0.15, 0.20, 0.25$

Allowing all combinations of x and y there are $x \times y = 169$ filter rules

A.2 Moving average rules

n = number of months in a slow moving average = 2, ..., 18

m = number of months in a fast moving average = 1, ..., 6

b = fixed band multiplicative value = 0.01, 0.02, 0.03, 0.04, 0.05

c = number of months for the time delay filter = 2, 3, 4

Noting that m must be less than n , there are 87 combinations of m and n .

Total number of MA rules: $87 + b \times 87 + c \times 87 = 783$

A.3 Support and resistance rules

n = number of months in the support and resistance range = 6, ..., 18

b = fixed band multiplicative value = 0.01, 0.02, 0.03, 0.04, 0.05

c = number of months for the time delay filter = 2, 3

Total number of S & R rules: $13 + 13 \times b + 13 \times c = 104$